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Economic Impact of Natural Disasters

Wendala Gamaralalage Subhani Sulochana Keerthiratne

Submitted for the Degree of Doctor of Philosophy in Economics

University of Sussex

June 2017

Declaration

I hereby declare that this thesis has not been and will not be, submitted in whole or in part to another University for the award of any other degree.

The first paper entitled ‘Impact of Natural Disasters on Financial Development’ of this thesis is co-authored with my main Supervisor, Prof. Richard Tol, and is published in Economics of Disasters and Climate Change (Keerthiratne & Tol, 2017). The final publication is available at Springer via http://dx.doi.org/10.1007/s41885-017-0002-5. I hereby declare that the entire analysis was carried out by me under the guidance of Prof. Tol. I produced the first draft independently and incorporated the amendments suggested by him.

The second paper entitled ‘Foreign Aid Concentration and Natural Disasters’ of this thesis is co-authored with my Supervisors. I hereby declare that the entire analysis was carried out by me under the guidance of my Supervisors. I produced the first draft independently and incorporated the amendments suggested by them.

The third and final paper entitled ‘Impact of Natural Disasters on Income Inequality in Sri Lanka’ of this thesis is also co-authored with my main Supervisor, Prof. Richard Tol. I hereby declare that the entire analysis was carried out by me under the guidance of Prof. Tol. I produced the first draft independently and incorporated the amendments suggested by him.

Signature:

Wendala Gamaralalage Subhani Sulochana Keerthiratne

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DOCTOR OF PHILOSOPHY IN ECONOMICS

ECONOMIC IMPACT OF NATURAL DISASTERS

SUMMARY

This thesis which consists of three empirical papers examines the economic impact of natural disasters.

The first paper estimates the impact of natural disasters on financial development proxied by private credit. Employing a panel fixed effects estimator on a country-level panel data set covering 147 countries for the period from 1979 to 2011, it finds that companies and households get deeper into debt after a natural disaster in the short run. This effect is stronger in poorer countries whilst the effect is weaker in countries where agriculture is more important. In the long run, capital markets appear to improve. Findings are robust to alternative estimators, specifications, samples and data.

The second paper explores the impact of natural disasters on the concentration of charitable receipts, again using country-level panel data. This analysis uses disaster indices purely based on physical intensities of natural disasters, thus overcome common issue of endogeneity in disaster data. In the short run, disasters expand the number of categories under which countries receive foreign aid and reduce the dependence on a single donor. Disasters reduce the concentration of the aid portfolio of recipient countries as measured by Herfindahl-Hirschman index. Findings are robust across alternative estimators. The study presents evidence of long term effects, too.

The third paper studies the relationship between natural disasters and income inequality in Sri Lanka as the first study of this nature for the country. It constructs regional inequality indices from micro data for Sri Lanka. Natural disasters do not affect expenditure inequality, but reduce income inequality. Natural disasters decrease non-seasonal agricultural and non-agricultural income inequality but increase seasonal agricultural income inequality. Income of richer households is mainly derived from non-agricultural sources such as manufacturing and business activities and non-seasonal agricultural activities. Poorer households have a comparatively higher share of seasonal agricultural income.

Acknowledgements

I am truly blessed to have the best Advisors any PhD candidate could ever ask for. I am eternally grateful to Prof. Richard Tol for his invaluable and incomparable guidance, and especially, for accepting me as I am. You always believed in me and transformed me into a confident researcher. I express my sincere gratitude to Prof. Richard Tol and Dr. Sambit Bhattacharyya for their timely and firm advices, constructive comments, excellent support, motivation, tolerance, patience and empathy throughout my doctoral studies.

I left the University of Sussex after successfully completing my Masters in Economics as a totally satisfied student in every aspect. When it came to my PhD, Sussex was my first and only choice. I profusely thank my University, the Doctoral School and specifically, the Department of Economics, its faculty and staff for creating an enabling and pleasant environment for students to excel in their studies and to grow into skilful professionals.

I gratefully acknowledge the funding received from RISES-AM- EU Research Project through Prof. Richard Tol for my PhD studies. I am much obliged to my employer, the Central Bank of Sri Lanka for providing me with additional funding and leave to pursue my PhD. I am also thankful to EM-DAT, the International Disaster Database, Belgium and the Department of Census and Statistics, Sri Lanka for providing me with data.

I thank Ayoni, Sajee, Sarah, all my friends, and my colleagues at Sussex and the Central Bank for being there for me whenever I needed you. I greatly value your friendship.

Thanks so much Amma and Thathi for your life-long blessings, encouragement, trust, help and care. Thanks my sisters and brother for all the support and love throughout.

My dearest children Seth and Sewmini, I am so proud to be your mother. Thanks so much for sharing equally the joys and sorrows of this PhD journey with me. If it were not for your understanding and support, my PhD would have been limited to a mere dream.

Sanjiv, the best husband ever, you are the inspiration of my life. Willingly bearing my absence, you travelled thousands of miles across the oceans every two-three months to see us. I am indebted to you for your immeasurable love, faithfulness, countless sacrifices and selfless support. It’s payback time. This PhD is for you!

My PhD journey gave me another fulfilling opportunity to realise with agape that everything is possible with God!

Contents

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List of Acronyms and Abbreviations

CBSL – Central Bank of Sri Lanka

CPIA – Country Policy and Institutional Assessment

EM-DAT – International Disaster Database

FDI – Foreign Direct Investment

GDP – Gross Domestic Product

GMM – Generalised Method of Moments

GNI – Gross National Income

HCI – Head Count Index

HHI – Herfindahl-Hirschman Index

HIES – Household Income and Expenditure

IFS – International Financial Statistics

IMF – International Monetary Fund

IQ^4R – Inter quartile range

IQ^5R – Inter quintile range of average income

ODA – Official Development Assistance

OECD – Organisation for Economic Co-operation and Development

OLS – Ordinary Least Squares

PPP – Purchasing Power Parity

PWT – Penn World Tables

Q1 – First quintile

Q2 – Second quintile

Q3 – Third quintile

Q4 – Fourth quintile

Q5 – Fifth quintile

Rs. – Sri Lankan rupee

U.S. – United States

UNISDR – United Nations Strategy for Disaster Reduction

US$ – United States dollar

VEI – Volcanic Explosivity Index

1 Introduction

Natural disasters have notably negative impacts on people (Hallegatte, Vogt-Schilb, Bangalore, & Rozenberg, 2017, p. 20). The impact of natural disasters may vary according to the disaster magnitude, intensity, frequency, risk, extent of the exposure and duration, and vulnerability[1]. Natural disasters cause a serious disruption to the functioning of a community or society through loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental degradation (UN General Assembly, 2009).

Natural disasters adversely impact economies in general and negatively affect growth. Hochrainer (2009) finds significant negative consequences of natural disasters on GDP. Raddatz (2007, 2009) also finds that climatic disasters reduce real GDP per capita. With evidence from Central American and Caribbean regions, Strobl (2012) shows that hurricanes negatively impact economic growth. When measured by property damage, natural disasters have negative effects on the macro-economy (Noy, 2009). Using natural disaster data purely based on physical intensities of such disasters, Felbermayr and Gröschl (2014) establish that natural disasters lower GDP per capita with low and middle income countries experiencing higher losses. Natural disasters are a drive for poverty and keep or pull back people into poverty; also, natural disasters impede economic development and hinder poverty reduction (Hallegatte et al., 2017). Sometimes, negative effects of natural disasters not only escalate poverty and deprivation in the short run but

[1] The UNISDR defines

a) Disaster risk as the potential loss of life, injury, or destroyed or damaged assets which could occur to a system, society or a community in a specific period of time, determined probabilistically as a function of hazard, exposure, vulnerability and capacity;
b) Exposure as the situation of people, infrastructure, housing, production capacities and other tangible human assets located in hazard-prone areas; and
c) Vulnerability as the conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards. (UNISDR, 2009)

also drive poor households into long-term poverty, triggering poverty traps (Carter, Little, Mogues, & Negatu, 2007). Conducting a meta-regression analysis on a large number of empirical studies, Klomp and Valckx (2014) conclude that there are genuine negative effects of natural disasters on economic growth.

Disasters destroy human and physical capital including infrastructure and thereby hamper economic activity. Natural disasters overwhelm economies and reduce welfare of the agents of the affected economy through mortality, morbidity and loss of physical assets. Subsequent to a natural catastrophe, the affected economy enters into a recovery phase. Recovery needs finances to rebuild the destroyed capital, and the recovery is faster and effective when finances are readily available. As poor countries are less prepared for and more vulnerable to disasters, they are in a disadvantageous position. Thus, foreign aid and credit have a major influence on their recovery. As developed financial systems can efficiently facilitate recovery financial requirement, financial development plays a key role. In the recovery phase, natural disasters can contribute to short term economic growth via reconstruction efforts. This is more if the replaced capital is more advanced than the destroyed. Therefore, short run economic impact of disasters could be mixed but probably negative (Tol, 2014, pp. 103-104). If climate change causes more and severe natural disasters, then it would be a matter of grave concern (Felbermayr & Gröschl, 2014, p. 93). In such a scenario, disaster risk management strategies and investments should be adjusted to account for future climate consequences (McDermott, 2016).

However, some scholars suggest a positive correlation between natural disaster frequencies and economic growth (Albala-Bertrand, 1993; Dacy & Kunreuther, 1969; Skidmore & Toya, 2002). In particular, investigating long-run effects of natural disasters, Skidmore and Toya (2002) find that climatic disasters are positively correlated with economic growth.

Severe natural disasters are destructive and costly. Their occurrence is beyond human control and their negative economic consequences are mostly unavoidable, especially for poor countries. Appreciating the major global impact of disasters, nations have come forward together to reduce disaster risk through Sendai Framework for Disaster Risk Reduction (UNISDR, 2015). As Noy, Managi, and Hallegatte (2017) point out, disasters play a key role in health, public finance, labour markets, development and other economic areas. As such, it is worthwhile to explore the impact of natural disasters on different economic aspects of development.

This thesis focuses on natural disaster consequences under three themes. First two papers analyse the disaster impact at macro level on financial development and foreign aid concentration, respectively, using cross country panel data sets. The final paper focuses on micro data and studies how natural disasters affect income inequality at regional level in a lower middle income country, namely Sri Lanka.

Generally, natural disasters reduce economic growth. This effect is more pronounced in countries where there are weak capital markets. Therefore, in the aftermath of natural disasters, it is essential to have quick and unconstrained access to finances for smooth and speedy recovery. Tol and Leek (1999) show that recovery finances could be acquired through assistance (credit or aid), savings and insurance. Thus, a stronger financial sector is important (Skidmore, 2001). Infrastructure can be easily reconstituted when there are well-functioning financial markets (Gignoux & Menéndez, 2016). Therefore, the level of financial development plays a key role. Expanding financial inclusion is one way of reducing well-being losses of natural disasters (Hallegatte et al., 2017). McDermott, Barry, and Tol (2014) find a significant negative impact of natural disasters on economic growth which is mitigated by higher credit.

In this background, the first paper of this thesis estimates the impact of natural disasters on financial development proxied by private credit. Apart from a study of Klomp (2014) which focuses on disaster impact on financial fragility as measured by banks' distance to default, to my knowledge, there is no other study to explore the impact of natural disasters on financial development. Therefore, the first paper of this thesis contributes to the existing literature by bridging a gap.

The analysis is based on a country-level panel data set covering 147 countries for the period from 1979 to 2011. Disaster data for this paper are obtained from EM-DAT, the International Disaster Database (Guha-Sapir, Below, & Hoyois, 2014). The variable of interest, disaster measure is constructed as the percentage of population affected due to all natural disasters in a country year. As Čihák, Demirgüç-Kunt, Feyen, and Levine (2012) illustrate, financial development has many facets. Financial development is indicated by higher level of access to, depth, efficiency and stability of financial institutions and markets. Widely used credit variable, i.e., the domestic credit to the private sector by deposit money banks as percentage of GDP (Čihák, Demirgüč-Kunt, Feyen, & Levine, 2013) is used to calculate per capita credit to be used in the analysis to proxy financial development. Credit measure is chosen given its wide data coverage, and the vital role played by private credit. Nevertheless, as financial markets are less well developed in low-income countries, the role played by formal credit in disaster consequences might be small.

Employing a panel fixed effects estimator as the main estimation tool, the paper finds that companies and households get deeper into debt after a natural disaster. This effect is stronger in poorer countries whilst the effect is weaker in countries where agriculture is more important. The magnitude of per capita credit varies across countries regardless of their per capita income. Hence, the real impact of disasters on credit as a share of prevailing per capita credit is country specific as well as time specific. These findings are robust to alternative estimators, specifications and samples. Considering the potential endogeneity issue of disaster data of EM-DAT, the analysis is repeated using an alternative disaster data set i.e., the ifo GAME data (Felbermayr & Gröschl, 2014) which is purely based on physical intensities of natural disasters. This exercise also yields consistent results. Private credit is only one dimension of financial development and financial markets are less well developed in poor countries which are more vulnerable to disasters. Thus, the immediate impact of natural disasters is better interpreted as households getting (further) into debt rather than as financial development, but we find longer term impacts too that indicate an expansion of credit availability.

The second empirical paper explores the impact of natural disasters on foreign aid concentration. Natural catastrophes bring in devastating economic episodes for countries through destruction. Sudden and large damages to infrastructure and physical capital losses paralyse governments eroding their capacity for reconstruction. As such, foreign aid can play a vital role in rebuilding after a severe natural disaster by fulfilling recovery financial requirements.

Natural disasters attract more foreign aid owing to various donor motives (Becerra, Cavallo, & Noy, 2014, 2015; Wei, Marinova, & Zhao, 2014; Wood & Wright, 2016). Although, it is expected donors to donate disaster related donations mainly on humanitarian motives, in practice, humanitarian aid is influenced by historical, political, cultural, religious or other pre-disaster connections donors have with recipients. For instance, analysing U.S. foreign disaster data from 1964 to 1995, Drury, Olson, and Belle (2005) highlight that U.S. foreign disaster assistance is strongly political, specifically at the disbursement compared to the allocation.

Yang (2008) shows that natural disasters considerably increase foreign aid. This is more when the international media coverage is broader for the disaster event. This aid supposedly facilitates speedy and smooth recovery and reconstruction after natural disasters. However, there is evidence also to suggest that past foreign aid flows suppress the political willingness to invest on disaster prevention and mitigation intentions (Raschky & Schwindt, 2016).

Whatever the underlying motive is, it is obvious natural disasters to enhance disaster related aid which may be aimed at emergency, disaster relief and even preparedness. However, if disasters can attract aid aimed at other development categories such as health, education, industry, etc., apart from disaster related aid, it can be expected this to enable recipient countries to invest in a vast range of development areas. If disasters influence countries to attract aid from more donors, recipients' donor base will be expanded. This will reduce single donor dependence and it can be expected this to strengthen the external network of the recipients from which recipients can seek support for development. In such a scenario, natural disasters reduce aid concentration of recipients. It can be expected that reduced aid concentration would facilitate economic growth through broadened investments and the support of a robust external network. However, the literature on the fragmentation of aid shows that, typically, aid is less effective in promoting economic development when it comes from many sources and is spread over many programmes (Gehring, Michaelowa, Dreher, & Spörri, 2017; Kimura, Mori, & Sawada, 2012; Oh & Kim, 2015; Sumner & Glennie, 2015). The second empirical paper thus shows that, besides the negative effect of natural disasters on economic growth, natural disasters also have a negative impact on development aid.

To my knowledge, no one has looked at the relationship between natural disasters and aid concentration, before. The only related study I know is Becerra et al. (2015) which presents some evidence of cross-sectorial substitution where donors sometime decrease aid aimed at other sectors in order to increase humanitarian aid given to the same recipient. Thus, this study allows me to contribute to the literature.

I examine the impact of natural disasters on the concentration of charitable receipts using country-level panel data for the period from 1979 to 2010. Natural disaster data used in this analysis are taken from the ifo GAME data (Felbermayr & Gröschl, 2014). It contains disaster indices which are purely based on physical intensities of disasters and strictly exogenous to social and economic conditions of countries. Therefore, they overcome entirely the common issue of endogeneity in natural disaster data. Using panel fixed effects estimator, I show that natural disasters enhance the diversification of aid categories, increase the number of donor entities and reduce aid concentration as measured by Herfindahl-Hirschman index (Hirschman, 1964) of recipient countries in the short run. Findings are robust to various checks. In the long run also, I observe statistically significant negative impact of natural disasters on foreign aid concentration.

Although, ifo GAME data do not suffer from endogeneity problem, one can argue that disasters can be considered as real natural disasters only when they cause losses to the human beings (Dacy & Kunreuther, 1969, p. 3). Therefore, I repeat my analysis using the disaster measure constructed using EM-DAT data for my first paper as discussed above, i.e., the percentage of population affected due to all natural disasters in a given year. This analysis also yields consistent results supporting original findings of this paper.

Natural disasters disproportionately affect the poor. Hallegatte et al. (2017, p. 4) recognise five underlying reasons for this. They are, overexposure; higher vulnerability; less ability to cope and recover; permanent impacts on education and health; and effects of risk on savings and investment behaviour. It is therefore often assumed that natural disasters increase income inequality. However, as Karim and Noy (2016) show, currently, there is only a little research on this matter. I contribute with my third and final paper which investigates the relationship between natural disasters and income inequality in Sri Lanka, as the first study of this nature for the country.

Generally, the poor households are more vulnerable to disasters and they bear disaster damages at a higher cost compared to the rich (Karim & Noy, 2016). The poor are more likely to have irregular income, so that every disruption, either due to the disaster directly or dealing with the aftermath, means a loss in income for them. The poor may be more vulnerable to loss of income due to their inability to engage in work and the unavoidable sale of income deriving capital assets as a coping strategy. If poorer households are less prepared for disasters; the poor live in disaster prone areas and homes that are more likely to be damaged; and receive earnings mainly from sectors such as weather dependent traditional agriculture which are more likely to face downturn, poor would bear higher income losses compared to the rich. Accordingly, natural disasters could give rise to greater income inequality.

In his cross country analysis, Yamamura (2015) finds that natural disasters increase income inequality. However, as disaster impact on households depends on country characteristics, cross country studies do not reveal the real picture (Karim & Noy, 2016). Therefore, country-level studies are required in this field.

Among the few such studies so far, Bui, Dungey, Nguyen, and Pham (2014) find that natural disasters increased income inequality among households in Vietnam in 2008. However, in terms of the findings of Abdullah, Zander, Myers, Stacey, and Garnett (2016), income inequality was decreased after the Cyclone Aila in Bangladesh in 2009. Feng, Lu, Nolen, and Wang (2016) did not find a change in income inequality among households due to 2008 Sichuan earthquake despite the 14% reduction in household income.

Although these findings may appear to be surprising, at subsistence level, people possess little that can be lost to a natural disaster. However, losses for the richer may be greater as disasters destroy their physical assets and negatively affect small businesses. Contracted wage earners are less likely to be affected by disasters. On the other hand, disasters may open up new informal financial opportunities for unskilled labour. Therefore, evidence on the impact of natural disasters on income inequality is mixed.

As Sri Lanka is a lower middle income country constantly faced by different natural disasters such as floods, droughts, storms and earth slides due to its geographical features and location, Sri Lanka provides a good case study. The analysis uses a unique panel data set constructed for the purpose of the paper. It contains district inequality measures based on household income reported in six waves of the Household Income and Expenditure Survey of Sri Lanka during the period between 1990 and 2013, data on disaster affected population and other economic and social indicators.

Employing a panel fixed effects estimator, I find that contemporaneous natural disasters and their immediate lags substantially decrease inequality in per adult equivalent household income as measured by the Theil index. Findings are robust across various inequality metrics, sub-samples and alternative estimators such as Ordinary Least Squares and System GMM. However, natural disasters do not affect household expenditure inequality. Either households behave as if they have a permanent income or all households reduce their expenditure proportionately irrespective of their income level in responding to natural disasters.

My data allow me to decompose income inequality into components of income so that mechanisms are understood better. This exercise shows that the reduction in income inequality is not derived through enhanced receipts or remittances. Natural disasters decrease non-seasonal agricultural income inequality and non-agricultural income inequality. But, disasters increase seasonal agricultural income inequality. This is explained by the fact that income of richer households is mainly derived from non-agricultural sources such as manufacturing and business activities and non-seasonal agricultural activities. In contrary, poorer households have a higher share of agricultural income.

The rest of the thesis is structured as follows. The second chapter examines the impact of natural disasters on financial development proxied by private credit. The third chapter explores the influences natural disasters have on foreign aid concentration of aid recipient countries. The fourth chapter investigates the impact of natural disasters on income inequality in Sri Lanka. The fifth and final chapter concludes.

2 Impact of Natural Disasters on Financial Development

2.1 Introduction

Natural disasters are inherently destructive, disruptive and costly in the short run, and may hamper economic growth too. Vice versa, poorer countries, and particularly financially underdeveloped countries are more vulnerable to natural disasters. This paper contributes to the study of the nexus of disasters and growth by estimating the impact of natural disasters on financial development.

The literature on the impact of natural disasters on economic growth is as yet inconclusive. Natural disasters are seen as a major impediment for global development efforts (UNISDR, 2002) and the resolution dated 18 February 2009 adopted by the General Assembly of the United Nations (UN General Assembly, 2009) stresses the fact that the impacts of natural disasters heavily hinder the achievement of internationally agreed development targets. Sometimes negative effects of natural disasters not only escalate poverty and deprivation in the short run but also drive poor households into long-term poverty, triggering poverty traps (Carter et al., 2007).

Although natural disasters are considered as negative for growth in general (Felbermayr & Gröschl, 2014; Raddatz, 2007; Strobl, 2012), some literature suggest a positive correlation between natural disaster frequencies and economic growth (Albala-Bertrand, 1993; Dacy & Kunreuther, 1969; Skidmore & Toya, 2002).

The level of financial development plays a key role. Specifically, in the recuperation subsequent to a disaster, it is necessary to have quick and unconstrained access to finances for immediate and smooth recovery. If the recovery investments bring in better and advanced technology, it not only ensures the speedy recovery but also paves the way for a higher economic growth. Insurance claims, own savings, aid and grants from the government and third parties, third party investments and indebtedness are the means to meet this financial need. There is a higher propensity to save in disaster vulnerable countries like Japan (Skidmore, 2001). As Tol and Leek (1999) point out required finances can be acquired through assistance (credit or aid), savings or insurance. In reducing economic damages caused by disasters, a strong financial sector is therefore important (Toya & Skidmore, 2007). As Gignoux and Menéndez (2016) highlight, it is possible to reconstitute publicly and privately owned infrastructure capital if there are well-functioning financial markets. If finances are readily available, it facilitates the speedy recovery which in turn enhances the development and regaining of the pre-disaster economic growth.

Countries with higher levels of domestic credit better able to withstand and endure natural disasters without affecting their economic output much (Noy, 2009). McDermott et al. (2014) find that natural disasters have a significant negative contemporaneous impact on economic growth which is mitigated by higher credit.

This raises the question whether natural disasters also affect financial development of an economy. Klomp (2014) highlights that natural disasters increase the likelihood of banks' default. Apart from this piece of work, which focuses on bank Z-scores and not on financial development *per se*, we do not find any other study in the existing literature which explores the impact of natural disasters on financial development. Hence, we probe the relationship between natural disasters and financial development.

In such an analysis one cannot completely rule out the endogeneity between financial development and the impact of natural disasters. For instance, Von Peter, Von Dahlen, and Saxena (2012) find that negative macroeconomic impact of natural disasters is mainly derived through uninsured losses. When the insurance rate is high, economic damages associated with disasters tend to be low.

Accordingly, in this paper we explore whether there is any impact of natural disasters on financial development proxied by credit, if so in which direction and in what magnitude and how it depends on other economic factors. At a broader level, financial development can be defined as the improvement in the quality of five key financial functions: (1) producing and processing information about possible investments and allocating capital based on these assessments; (2) monitoring individuals and firms and exerting corporate governance after allocating capital; (3) facilitating the trading, diversification, and management of risk; (4) mobilising and pooling savings; and (5) easing the exchange of goods, services, and financial instruments (Čihák et al., 2013, p. 9). Čihák et al. (2013) highlight level of access to, depth, efficiency and stability of financial institutions and markets. They present a 4x2 matrix of financial system characteristics and compile panel data which can be used as proxies for financial development. However, credit availability to the real sector by domestic banks as a percentage of GDP is used most in the literature. Its wide data coverage, and the vital role played by private credit may be the reasons for this.

We also use private credit as proxy for financial development in our analysis. This measure reflects the extent to which households and companies depend on the banking system for their financial needs and the magnitude of financial intermediation facilitated by the banking system in return (Giuliano & Ruiz-Arranz, 2009). Private credit can be considered as a reliable source to meet immediate financial requirement in the recovery phase of a disaster, especially for low-income countries where private savings rate and insurance penetration are considerably low. We acknowledge that private credit is only one dimension, i.e. financial depth of financial development which has many facets as discussed above. Further, poor countries are more vulnerable to natural disasters and suffer disproportionately from disaster damages as opposed to rich countries. As financial markets are less well developed in low-income countries, the role played by formal credit in disaster consequences might be small, therein. Section 5 discusses alternative indicators of financial development, but data availability is problematic. We are therefore compelled to use credit measure as the main proxy for financial development in our analysis.

2.2 Empirical Analysis

2.2.1 Data

The source of natural disaster data for this study is EM-DAT, the International Disaster Database maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the *Université Catholique de Louvain* in Brussels, Belgium (Guha-Sapir et al., 2014). The EM-DAT database contains *inter-alia* data on world-wide natural disasters occurred since 1900. Over 13,000 natural disaster events occurred in about 220 countries from 1900 to 2014 are reported in the database. As per the database, from 1979 to 2011, the period on which the instant study is focused for the reasons of data quality and availability, over 10,000 natural disaster events have occurred in 219 countries affecting more than six billion people.

EM-DAT classifies natural disasters into subgroups, namely, biological, climatic, hydrological, geophysical, meteorological and extraterrestrial disasters. Each natural disaster subgroup contains data on relevant types and sub-types of natural disaster events.

For a natural disaster to enter into the EM-DAT database, at least one of the setout criteria needs to be fulfilled, i.e., reported death toll of 10 or more, 100 people reported affected, a call for international assistance or the declaration of state of emergency. As highlighted by Miao and Popp (2014), these are arbitrary thresholds. There is a tendency for national governments to exaggerate the disaster damage in reporting as a strategy for attracting external aid, especially in developing countries (Noy, 2009). Still, EM-DAT is the source of data that has been used widely in disaster literature.

The EM-DAT database contains disaster outcomes measured as the number of total deaths, number of people affected (injured, became homeless, displaced or affected otherwise) and the total monetary damage caused by a disaster. The economic data may be gathered by the individuals who attend the affected area primarily with the intention of providing medical care and physical aid. Therefore, they may lack the expertise to estimate of the economic loss. Of the numbers of people killed and affected, the preferred variable is the number of people affected. In some instances, even a severe disaster may not kill as shown by Gassebner, Keck, and Teh (2010), Cavallo and Noy (2011) and Klomp (2014). Hence, in this study, the number of people affected by natural disasters in a country year is chosen as the variable of interest. Accordingly, our analysis is limited to disasters where there are reported affected population. Following Noy (2009), the disaster variable is normalised as the “percentage of population affected”.

There are 2,712 country-years with at least one disaster. On average, disasters affect 3.6% of the population in a country-year and the maximum percentage of population affected by natural disasters in a single country-year surpasses 150%. Hydrological disasters are the most common natural disaster. However, climatic disasters affect the highest percentage of population, with meteorological disasters next in line. See Table 2.1.

Table 2.1: Severity of disasters by % of population affected

Disaster Type	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
All Disaster Events	2,712	3.64	11.27	1.65e-06	156.78
Biological	710	0.23	1.36	6.85e-07	25.16
Climatic	522	8.98	18.11	2.13e-06	118.47
Hydrological	1,718	1.21	3.62	1.65e-06	45.24
Geophysical	528	0.67	3.37	5.03e-07	48.51
Meteorological	861	3.01	11.59	1.39e-06	156.78

The number of people affected by a disaster depends on the nature of the disaster as well as on the underlying socio-economic status and disaster management strategies of the affected economy, leading to endogeneity in models that quantify the economic impact of natural disasters (Kellenberg & Mobarak, 2008; McDermott et al., 2014; Sen, 1983; Tol & Leek, 1999). In order to reduce the endogeneity problem, while Noy (2009) and Klomp (2014) develop a count disaster measure, McDermott et al. (2014) construct a binary disaster variable imposing a threshold of 0.5 percent on the fraction of population affected to capture only the relatively severe disasters in the model. As a robustness check, McDermott et al. (2014) carry out their analysis using a binary disaster variable constructed without imposing any such threshold. They admit the fact that the binary variable reduces the variation of data and the explanatory power of the model. In spite of this they opt for a binary disaster variable as it reduces not only the influence of measurement error in disaster data on the analysis but also the possibility of results are being driven by outliers at the upper bound of the disaster data distribution. However, by doing this they equalise minor disaster events which affect a very few individuals with severe disaster events which affect hundreds of thousands of people. Further, it can be argued that the imposition of an arbitrary threshold to segregate large disasters would cause biases in the estimates. Yet, it is not less common in disaster studies to adopt such decision rules to isolate severe disasters to include in the model. For instance, Becerra et al. (2014) and Klomp (2014) deploy such decision rules to limit their investigation to major disasters. Exploring disaster effects on bank solvency, Klomp (2014) limits his sample to 170 severe disasters which caused highest economic damage and the time period from 1997 to 2010 in quantifying the impact of natural disasters on bank Z-score which reflects banks' distance to default.

Since there is a clear trade-off in using a binary disaster variable with or without a decision rule, the current analysis employs a continuous disaster variable, namely the percentage of population affected by natural disasters in a country year. Nevertheless, as a supportive identification strategy and a robustness check, the baseline model is run using a binary disaster variable with various thresholds to segregate severe disasters in constructing the disaster dummy, as more fully described later on, to see whether it derives consistent results.

This paper explores the impact of natural disasters on financial development. A widely used private credit measure is chosen to proxy financial development given its broad data coverage in space and time, although it only measures the depth of financial institutions.

Data on private credit by deposit money banks as a percentage of gross domestic product (GDP) are obtained from the Global Financial Development Database, an open data source of the World Bank constructed by Čihák et al. (2013) covering 205 economies from 1960 to 2011. They have constructed said credit variable using the International Financial Statistics (IFS) published by the International Monetary Fund (IMF). It is defined as the domestic private credit to the real sector by deposit money banks as percentage of GDP. Accordingly, private credit does not include credit issued to governments, government agencies and public enterprises, and credit issued by central banks. This credit measure is used to construct the dependent variable of our model, i.e., private credit per capita. We use per capita credit, rather than credit per GDP, because per capita GDP is included in the regression model as a key explanatory variable. We thus avoid GDP being present on both sides of the equation. Furthermore, the variation in private credit per GDP the data may be due to the variation either in credit *per se* or in GDP; and both may vary in response to a natural disaster. The use of per capita private credit also resolves this issue. The measure of private credit as a percentage of GDP is converted to constant 2005 US dollar per capita credit using constant 2005 US dollar GDP data, thus accounting for dollar inflation over time. The analysis is repeated using purchasing power parity (PPP) constant 2005 US dollar per capita credit, accounting for price differences across countries.

The level of credit depends on the level of income as that determines credit necessity and credit worthiness. Accordingly, the natural log of the output based real GDP per capita of the current year enters the regression along with its interaction with the disaster variable as regressors. Constant 2005 US dollar per capita GDP and PPP constant 2005 US dollar per capita GDP are calculated using relevant data contained in the World Bank's World Development Indicators and the Penn World Tables (PWT) Version 8.0 database (Feenstra, Inklaar, & Timmer, 2013), respectively.

Political institutions play a vital role in disaster mitigation, which is at least to some extent a public good. Plumper and Neumayer (2010) argue that the polity2 variable from the Polity IV Project is the most appropriate and popular measure of a country's political regime. Polity2 indicates openness of a country's political institutions. In the Polity IV database, the democracy indicator (democ), which varies on an eleven-point scale (0-10), represents the institutionalised democracy of a state. It depends on 3 elements which cover the democratic rights of citizens and the constraints on the executive in exercising its powers. Similarly, the institutionalised autocracy indicator (autoc), also an eleven-point scale (0-10), measures the institutionalised authoritarianism of the regime of a country. These two scales democ and autoc do not share any contributor categories in common. The value of polity2 is obtained by subtracting the autocracy (autoc) from the democracy variable (democ). It ranges between +10 (strongly democratic) and -10 (strongly autocratic).

A country that heavily relies on agriculture, especially rainfed agriculture, can be expected to be particularly vulnerable to natural disasters, such as droughts, floods, and storms. Both the destruction of cultivations and livestock and the disruption of transport and trade would affect the demand for credit and creditworthiness. As such, agriculture share of the economy together with its interaction with disaster variable is included in the benchmark specification.

Data on the share of agriculture as a percentage of GDP and other controls such as inflation, government consumption as a percentage of GDP, share of trade as a percentage of GDP, net official development assistance (ODA) received as a percentage of gross national income (GNI), financial sector rating, lending interest rate, private savings rates and insurance penetration are taken from the World Bank's World Development Indicators. Data on resources of countries are obtained from the Wealth of Nations data series maintained by the World Bank.

The sample consists of 147 countries during 1979 to 2011. The panel is unbalanced. With the inclusion of more control variables sample size decreases due to non-availability of data. Post estimation summary statistics for the variables used in the baseline analysis are provided in Table 2.2.

Table 2.2: Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Disaster (% of Population Affected)	1.69	6.89	0	118.47
Credit per capita (constant 2005 US$)	6,547	15,583	0.85	163,982
GDP per capita (constant 2005 US$)	8,100	12,980	112	87,717
Polity2	3.01	6.78	-10	10
Share of Agriculture (as % of GDP)	17.46	14.76	0	73.48

2.2.2 Empirical Model

We employ a panel regression estimator with country and year fixed effects as the main estimation strategy in our analysis. Fixed effects estimator is chosen since country and year fixed effects control for time-invariant country heterogeneity and time-variant shocks that simultaneously affect all the countries, respectively. This reduces any potential endogeneity issue. The Hausman test (Hausman & Taylor, 1981) shows that the fixed effects estimator is preferred to the random effects estimator. Furthermore, country-fixed effects also arrest any selection biases which may arise due to over representation of poor countries in the disaster data distribution as a result of their higher vulnerability to disasters (McDermott et al., 2014). Year fixed effects capture the effects of time-varying factors common to all countries such as the global business cycle, global technological advancement and world-wide economic and financial crises. Time-fixed effects are jointly significant. Errors are clustered at country level as natural disasters are not evenly distributed across countries and also to obtain robust standard errors as a remedial measure for heteroscedasticity. Given the constraints on availability and reliability of data, the analysis is restricted to the time period 1979 – 2011. The baseline model covers 147countries.

The panel regression equation of the baseline model is as follows;

$$Credit_{it} = \beta_0 + \beta_1 Dis_{it} + \beta_2 Credit_{i,t-1} + \beta_3 lnGDP_{it} + \beta_4 Dis_{it} * lnGDP_{it} + \beta_5 Agrshr_{it} + \beta_6 Dis_{it} * Agr_{it} + \beta_7 Polity_{it} + \theta_i + \theta_t + \epsilon_{it} \tag{2.1}$$

Credit per capita valued at constant 2005 US$ in country *i* for year *t*, is the dependent variable. A lagged credit term is included as an explanatory variable because it can reasonably be assumed that the current credit level is heavily determined by its past level and to defend the existence of autocorrelation in the regression. However, as by construction lagged dependent variable and error term are correlated, one may argue that the use of a lagged dependent variable in the fixed effects estimator poses a serious econometric problem. Such use can cause negative biases on estimates for positive coefficients in short panels with small time periods. To overcome this issue the best remedy would be the use of a valid instrument variable, however, it is very hard to find such an instrument. As McDermott et al. (2014) show this is a serious concern only in the event the panel is short. They claim that the issue is being addressed by using a long panel of 29 years and they support their findings with consistent results obtained in dynamic panel estimators. Ours is an even lengthier panel of 33 years. We also get consistent results using System GMM. We obtain consistent results even when the specification is modelled without including the lagged dependent variable but including only disasters, logged GDP per capita and disaster-income interaction with and without further control variables as specified under the robustness checks.

Dis is our variable of interest: Disaster measured as the percentage of population affected due to all the natural disasters occurred in a single country year. As the percentage of population affected increases, it can be expected the private credit to rise as a result of higher demand for financing aimed at recovery, reconstruction and rehabilitation in the aftermath of a natural disaster. As private credit availability is an indicator of financial development, a positive coefficient on the disaster variable would establish positive effects of disasters on financial development, although it may also indicate people getting into debt after a disaster.

GDP is the logged GDP per capita in constant 2005 US$. It is included in the model as the level of credit clearly depends on income level. Demand for and the availability of credit are different in poor and rich economies. In poor countries, dependency on private credit appears to be much higher in the recovery phase of a natural disaster in that the private savings rate and insurance penetration are substantially lower.

The disaster variable is interacted with logged per capita GDP. We expect that a higher income reduces the need for debt-financing the recovery, because of higher savings and greater insurance cover. If so, the interaction term would be negative.

The share of agriculture in GDP and its interaction with disasters are included in the bench mark specification to capture the effect of economic structure beyond development. As a country's preparedness and management strategies for natural disasters depend on the political will and institutions of that country, we include polity2 as a control variable. Terms θ_i and θ_t are the country and year fixed effects, respectively; ϵ_{it} is the independently and identically distributed error term.

When using a longer panel, one has to be careful because non-stationarity might give rise to spurious results as suggested by Nelson and Plosser (1982). As one can suspect a unit root in the credit data, we estimate the model using various approaches: levels, levels with lagged dependent variable, long averages, first differences, and first differences with first differences in the controls. The key results are robust.

To ascertain medium-term dynamics of disasters, we include lags of disaster variable and its interactions with income and agriculture.

To show our original results are not driven by outliers, we repeat our regressions removing alternatively and jointly observations at the lower and upper bounds of the credit distribution and at the upper bound of the disaster distribution.

For identification, we assume that disasters are exogenous to credit. Although borrowed money can be used to fund protection against natural disasters, the probability is remote that contemporaneous credit affects vulnerability to disasters as it takes a long time for credit to be converted into effective and defensive disaster impact preventive or mitigating projects. The disaster exogeneity assumption is adopted by other disaster papers including Noy (2009), Raddatz (2007), Ramcharan (2007) and Skidmore and Toya (2002). If the exogeneity assumption does not hold, then the best solution to avoid reverse causality would be to employ a valid instrument. However, it is extremely difficult to find such an instrument (Noy, 2009).

Felbermayr and Gröschl (2014) present a new disaster database called ifo GAME Data. Their measures are purely based on the physical intensities of disasters making them exogenous to the economic condition of a country. We use GAME data as an alternative database to check validity of our findings.

Following McDermott et al. (2014) we construct a binary disaster variable, using various thresholds. A binary variable is less subject to potential reverse causality. We do this as a robustness check, as with a continuous disaster variable as we can be more precise in quantifying disaster effect on private credit.

Apart from binary disaster variable following Fomby, Ikeda, and Loayza (2013), we construct an impact variable which scales to the size of the disaster, but eliminates the smallest disasters. This approach reduces the weight of the distribution of disasters from being clustered around the very many, very minor disasters.

Following (Noy, 2009) we weigh our disaster measure in terms of the onset month. There is a likelihood for disasters which occurred in earlier months of the year to cause a bigger impact in the same year than disasters which occurred in later months.

We check against omitted variable bias by adding more control variables, such as macro stability, magnitude of the government spending, foreign links, which can be expected to have an influence on per capita credit. The inclusion of additional control variables is done at different stages. Firstly, we add main control variables one by one to the baseline model and subsequent to each addition, an interaction term of that control with the disaster variable is included so that their impact on the baseline model can be observed clearly. These main control variables are inflation which controls for macroeconomic stability of the country, government expenditure as a percentage of GDP and the trade share which reflects the degree of trade openness. Secondly, we control for other factors which seem to either stimulate or hinder private credit in connection with disasters, by using simple variant models of the baseline specification. Accordingly, we control for financial sector regulation using CPIA (Country Policy and Institutional Assessment) financial sector rating, non-life insurance premia volume as a share of GDP, lending interest rate, share of resource rent (including rent received on coal, oil gas, iron ore and minerals such as gold, silver, copper, etc. but not including rent on forestry) within the GDP, and share of forestry rent as a percentage of GDP and net official assistance received as a percentage of gross national income.

Apart from the panel fixed effect regression, different estimators are used, namely, ordinary least squares (OLS), quantile regression, and system generalised method of moments (GMM); see Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998) and Roodman (2009a and 2009b).

We measure per capita credit and GDP in constant 2005 US$ and so account for inflation. To control for differences in living standards we repeat the analysis using per capita credit and GDP measured in purchasing power parity (PPP) constant 2005 US dollars. We also rerun the regression using logged credit variable.

To eliminate any potential cross-sectional dependence given the spatial nature of disaster data, we use Driscoll-Kraay errors (Driscoll & Kraay, 1998) as they are robust to general forms of spatial dependence. We further explore the impact of different categories of natural disasters on private credit and we also run our regression for different geographical regions. Finally, we ascertain the impact of natural disasters on other measures which proxy for financial depth, access, efficiency and stability.

2.3 Results

Results of the baseline model are given in Table 2.3. We restrict attention to the marginal effect of natural disasters on private credit. Disasters show a significant positive effect on contemporaneous credit. However, this positive effect is dampened down by higher income. It appears that the disaster-agriculture interaction also yields a negative coefficient suggesting that the positive impact of disasters on credit is further mitigated by higher share of agriculture in the economy. However, as this interaction is significant only at the 10% level, we ignore it for the time being.

Table 2.3: Base model

	Dependent variable: Credit per capita
	Fixed Effects
Disaster (% Population Affected)	35.35**
	(14.08)
Lagged Credit per capita	1.00***
	(0.0172)
GDP per capita (in logs)	654.0***
	(176.3)
Disaster * ln GDP per capita	-4.669**
	(1.807)
Share of Agriculture	15.64**
	(7.006)
Disaster * Agriculture	-0.135*
	(0.0763)
Polity2	-1.064
	(5.273)
Observations	3,189
Number of Countries	147
R-squared	0.958

Notes: Annual data 1979-2011, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

A zero marginal effect of disasters on credit is seen in a country with an average per capita GDP of constant 2005 US$ 1,941 (standard deviation 1,016) per year. Table A.1 in the Appendix gives the impact for selected countries, evaluated at the country average over time. In a low income country like Burkina Faso, a one percentage point increase in the percentage of population affected by natural disasters will on average increase the contemporaneous per capita private credit by $8.33[2] or 17%[3]. However, in a high income country like Australia, when the disaster affected percentage of population increases by one percentage point, the contemporaneous per capita credit falls by $12.42 or 0.06%. Notwithstanding the fact that both countries have similar values for average population affected (2.3% and 2.8%, respectively) due to natural disasters, they see a divergent impact on private credit. Table A.2 in the Appendix shows the impact evaluated using 2011 figures.

Figure 2.1: Nominal effect of natural disasters on per capita credit (using 2011 values)

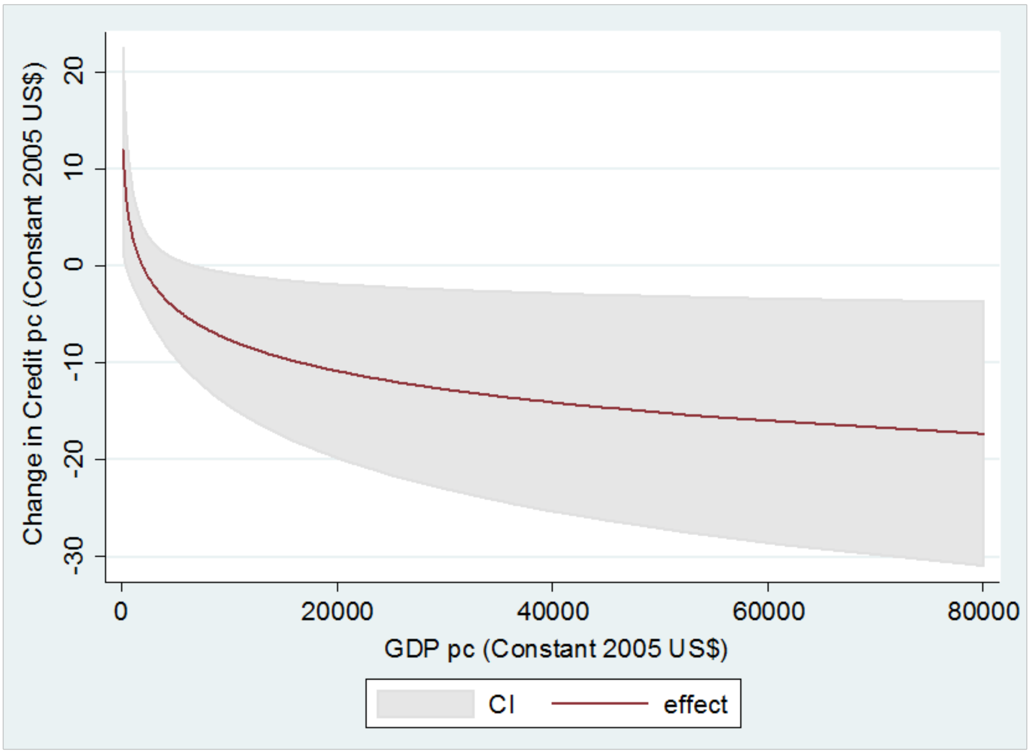


Figure 2.1 shows the absolute change in per capita credit, due to a one percentage point increase in the percentage of population affected by disasters in a single year, varies with per capita income, evaluated using 2011 data. There are 53 countries (out of 146 shown

[2] [35.35-(4.669*ln326)]
[3] (8.33/48*100)

in Figure 2.1) with per capita GDP below constant 2005 US$ 1,941 in 2011. As such, 53 countries lie below the per capita income of the point where the curve crosses the horizontal axis in Figure 2.1. The absolute effect is negative for many rich countries. It may be due to the fact that rich countries have access to insurance market and cover damages with insurance claims rather than getting into debt. Further, in the recovery phase after a natural disaster, ordinary debt financed investments might contract, as the housing market and hence the mortgage market slows down and as people postpone debt-financed purchases as they focus on recovery.

Figure A.1 in the Appendix shows this effect as a percentage of prevailing per capita credit. Figure A.2 in the Appendix shows the same on a map[4]. It appears that when it comes to credit, low income countries gain more from disasters compared to their rich counterparts.

[4] We used the Stata command spmap by Maurizio Pisati. See https://ideas.repec.org/c/boc/bocode/s456812.html

2.4 Robustness Checks

2.4.1 No Lagged Dependent Variable

We run the fixed effects estimator without the lagged dependent variable to address any concern about attenuation or Nickel bias. As above, we observe a positive effect of disasters on per capita private credit, which is moderated by disaster income interaction. These results hold also in the presence of control variables. See Table A.3 in the Appendix. Explanatory power falls substantially in the absence of the lagged dependent variable, as apparent from the R^2; recall that credit per capita is a stock variable.

2.4.2 Unit Root

Instead of using credit per capita in its level as the dependent variable, we use the first difference of credit per capita, again with a fixed effects estimator. In the base model, the lagged dependent variable is indistinguishable from unity. As shown in Table 2.4, this yields results consistent with those above.

As a next step, we take the first difference of the explanatory variables, except for the disaster variable and per capita income. Table A.4 in the Appendix shows the results, again consistent with those above.

2.4.3 Medium-Term Effects of Disasters on Credit

By averaging our annual data over five year and ten year periods, we ascertain the effect of disasters on credit in the medium-term. Results for the fixed effects panel estimator using five-year and ten-year averages are presented in Table 2.5, and Table A.5 in the Appendix, respectively. In addition, to test medium-term dynamic effect of disasters on credit, following McDermott et al. (2014) we run models that include up to 7 lags of disaster variable and its interactions with logged per capita GDP and the share of agriculture in GDP using annual data. Table 2.6 presents the sum of the resultant contemporaneous and lagged effects of disaster and its interaction with income for each model. We confine models to include lags only up to 7 as the disaster variable loses significance after 5 lags and the disaster-income interaction loses significance after 6 lags. It is apparent from the results that the sum of coefficients on the disaster variable increases with more lags compared to the base model reflecting persistency of disaster impact on credit. Qualitatively, the results are the same regardless of the number of lags included.

2.4.4 Outliers

To ensure that results are not driven by potential outliers, we remove observations at the top and bottom of the credit and disaster data distributions. Specifically, we remove the top and bottom 10% and then 20% of the credit distribution which brings down the range to 31 - 21,956 and 78 - 8,696, respectively, from original range of 0.845 - 163,982. With respect to disasters, we remove 27 and then 55 observations with highest percentage of population affected which brings down the range of disasters to 0 - 56% and 0 - 38%, respectively, from 0 - 118%. We also remove Tsunami year 2004; and 2004 and 2005 together as the Tsunami took place at Christmas. Table A.6 and Table A.7 in the Appendix, and Table 2.7 show the results, which are consistent with those above.

2.4.5 Alternative Database, ifo GAME Data

We use two alternative disaster indices namely ‘indexla’ and ‘disindexla’ constructed by Felbermayr and Gröschl (2014). These indices are clearly exogenous to economic and financial development. Indexla is the sum of physical intensity measures of disasters happened in a specific country in a specific year weighted by land area of the affected country. Disindexla is further weighted by respective inverse sample standard deviations. Table 2.8 shows results of the regressions using these disaster indices. Using the ifo GAME disaster data we again find a positive impact of disasters on private credit mitigated by higher income, supporting our original findings.

2.4.6 Additional Controls

As a further robustness check, control variables are included. See Table A.8 and Table A.9 in the Appendix. The addition of controls leads to consistent results and so does not invalidate the findings above. When controlling for inflation, government expenditure, international trade, financial sector rating, non-life insurance, lending interest rate, resource rent and forestry rent, the results for the disaster variable and its interaction with income do not change. However, the variables of interest lose significance in the presence of foreign aid. This may well be because foreign aid increases in response to natural disasters.

2.4.7 Alternative Estimators

We re-estimate the model using system GMM, ordinary least squares (OLS), and quantile regressions to test whether they yield consistent results.

Results of the baseline model using alternative estimation methods are presented in Table 2.9 (Columns 1-3). The results are consistent across the alternative estimators. Quantile regression also yields consistent results at all percentiles; see Table A.10 in the Appendix.

Table 2.4: Change in per capita credit as the dependent variable (fixed effects)

	Dependent variable: Change in credit per capita												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Disaster	**17.28****	**25.73****	**26.61*****	**12.26**	**21.41***	**35.31****	**38.22*****	**41.61*****	**41.05*****	**43.16*****	**36.53****	**36.49****	**36.79****
	(8.14)	(10.55)	(10.14)	(7.82)	(11.71)	(13.65)	(14.01)	(14.26)	(14.29)	(14.74)	(14.60)	(14.92)	(15.23)
GDP pc (in logs)	647.7**	604.4**	604.7**	712.3***	716.2***	652.8***	654.2***	659.2***	658.9***	708.4***	710.0***	701.2***	701.7***
	(289.6)	(295.4)	(295.6)	(178.8)	(179.5)	(152.7)	(153.2)	(155.0)	(155.0)	(170.6)	(170.6)	(169.4)	(169.7)
Dis * ln GDP pc	**-2.33****	**-3.69****	**-3.85****	**-1.75**	**-2.67***	**-4.66*****	**-5.04*****	**-5.38*****	**-5.33*****	**-5.52*****	**-5.60*****	**-5.59*****	**-5.48*****
	(1.18)	(1.58)	(1.51)	(1.15)	(1.47)	(1.75)	(1.78)	(1.80)	(1.80)	(1.85)	(1.88)	(1.89)	(2.05)
Polity2		-15.45**	-15.78**			-0.95	-1.22	-0.88	-0.88	0.88	0.86	0.87	0.89
		(7.13)	(7.25)			(6.04)	(6.09)	(6.39)	(6.40)	(6.98)	(6.99)	(6.96)	(6.96)
Dis * Polity2			0.13				0.11	0.09	0.08	0.12	0.11	0.12	0.10
			(0.11)				(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)
Agriculture Share				15.08**	15.35**	15.55**	15.60**	16.36**	16.31**	15.86**	15.75**	16.26*	16.31*
				(6.32)	(6.35)	(6.58)	(6.59)	(6.98)	(6.96)	(7.81)	(7.80)	(8.30)	(8.35)
Dis * Agriculture					-0.08	-0.14*	-0.15*	-0.18**	-0.19**	-0.22**	-0.16*	-0.16	-0.17**
					(0.076)	(0.076)	(0.080)	(0.081)	(0.081)	(0.087)	(0.085)	(0.094)	(0.085)
Inflation								0.0104	0.0103	0.0116	0.0114	0.0101	0.0102
								(0.0195)	(0.0193)	(0.0204)	(0.0204)	(0.0196)	(0.0197)
Dis * Inflation									0.012	0.010	0.018	0.018	0.016
									(0.017)	(0.020)	(0.019)	(0.019)	(0.019)
Govt. Expenditure										-9.72	-10.25	-10.26	-10.37
										(8.77)	(8.86)	(8.98)	(9.00)
Dis * Govt. Exp.											0.348	0.338	0.395
											(0.211)	(0.209)	(0.260)
Trade Share												1.217	1.244
												(3.880)	(3.912)
Dis * Trade													-0.017
													(0.030)
Observations	4,155	3,614	3,614	3,671	3,671	3,189	3,189	3,130	3,130	3,047	3,047	3,041	3,041
R-squared	0.028	0.059	0.059	0.025	0.025	0.052	0.052	0.053	0.053	0.055	0.055	0.055	0.055
No. of Countries	176	152	152	170	170	147	147	145	145	145	145	145	145

Notes: Annual data 1979-2011, except where first observation lost due to differencing. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Aggregated (five-year) data

	Dependent variable: Credit per capita								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Disaster	**727****	**839***	**1,025****	**1,097****	**1,086****	**1,008****	**1,032****	**1,207****	**1,137****
	(331)	(450)	(403)	(423)	(420)	(416)	(421)	(488)	(481)
GDP per capita (in logs)	4,779*	4,420*	4,522*	4,369*	4,398*	4,553*	4,555*	3,918*	3,874*
	(2,48)	(2,55)	(2,59)	(2,62)	(2,64)	(2,58)	(2,58)	(2,25)	(2,24)
Disaster * ln GDP per capita	**-93****	**-111***	**-140****	**-150****	**-149****	**-137****	**-135****	**-153****	**-136****
	(45.85)	(65.15)	(58.03)	(60.58)	(60.42)	(60.64)	(61.23)	(68.01)	(66.38)
Polity2		-401***	-434***	-469***	-468***	-504***	-503***	-515***	-515***
		(99)	(104)	(113)	(113)	(118)	(118)	(118)	(118)
Disaster * Polity2			14.77**	15.13**	15.36**	12.42*	12.81*	12.85*	11.70
			(6.81)	(7.05)	(7.13)	(7.29)	(7.21)	(7.38)	(8.07)
Inflation				0.87**	0.73*	0.74**	0.74**	0.82**	0.85**
				(0.41)	(0.40)	(0.35)	(0.35)	(0.34)	(0.36)
Disaster * Inflation					0.28	0.41	0.39	0.39	0.34
					(0.36)	(0.38)	(0.38)	(0.41)	(0.39)
Government Expenditure						205**	208**	178*	170*
						(84)	(89)	(92)	(93)
Disaster * Govt. Expenditure							-2.49	-5.99	-2.01
							(7.15)	(8.14)	(8.24)
Trade Share								50.17	51.82
								(40.20)	(41.15)
Disaster * Trade									-1.22
									(1.07)
Observations	830	724	724	708	708	690	690	690	690
R-squared	0.175	0.226	0.227	0.236	0.236	0.247	0.247	0.260	0.260
Number of Countries	175	150	150	148	148	148	148	148	148

Notes: Aggregated data in periods, 1979-2008. All models include a constant term, country and time fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.6: Dynamics of disasters and credit: Cumulative lagged effects (fixed effects)

	Dependent variable: Credit per capita							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No Lags	1 Lag	2 Lags	3 Lags	4 Lags	5 Lags	6 Lags	7 Lags
Disaster	35.35**	47.69**	74.59**	102.34**	132.49**	118.94**	82.24	47.47
	(2.51)	(2.28)	(2.38)	(2.19)	(2.23)	(1.99)	(1.33)	(0.68)
Dis * ln GDP pc	-4.669**	-6.124**	-9.118**	-12.424**	-16.235**	-15.461**	-12.275*	-9.615
	(-2.58)	(-2.42)	(-2.54)	(-2.38)	(-2.47)	(-2.38)	(-1.86)	(-1.31)
Observations	3,189	3,156	3,068	2,976	2,882	2,784	2,684	2,579
R-squared	0.958	0.957	0.954	0.950	0.947	0.944	0.940	0935
Countries	147	146	144	144	144	144	144	143
AIC	54890	54339	52870	51332	49764	48086	46400	44613
BIC	55121	54587	53129	51602	50044	48377	46701	44924

Notes: Annual data 1979-2011, except where lost due to lags. All models include a constant term, country and year fixed effects. All models also include other regressors of base model with applicable lags of disaster and its interactions. Reported coefficients and t-stats are the summed contemporaneous and lagged effects. Errors clustered at the country level. *t*-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.7: Models without credit and disaster outliers (fixed effects)

	Dependent variable: Credit per capita		
	(1) w/o credit bot. & top 20% and disaster top 55 obs	(2) w/o credit bot. & top 20%, yr 2004 and disaster top 55 obs	(3) w/o credit bot. & top 20%, yrs 2004-05 and disaster top 55 obs
Disaster (% Pop. Affected)	23.65***	28.31***	27.41***
	(8.551)	(8.572)	(8.418)
Lagged Credit per capita	1.005***	1.004***	1.003***
	(0.0226)	(0.0223)	(0.0214)
GDP per capita (in logs)	277.9***	285.0***	282.4***
	(54.02)	(54.45)	(52.25)
Disaster * ln GDP per capita	-3.137***	-3.853***	-3.791***
	(1.112)	(1.098)	(1.070)
Share of Agriculture	3.962	4.331*	3.954*
	(2.552)	(2.452)	(2.324)
Disaster * Agriculture	-0.0692	-0.0524	-0.0262
	(0.0651)	(0.0656)	(0.0716)
Polity2	1.551	1.714	1.623
	(1.740)	(1.808)	(1.814)
Observations	1,866	1,786	1,707
R-squared	0.937	0.938	0.939
Number of Countries	109	108	108

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.8: Disaster indices from ifo GAME Data

	Dependent variable: Credit per capita	
	(1) indexla	(2) disindexla
Disaster Index	4,588**	4,931**
	(1,752)	(2,368)
Lagged Credit per capita	1.028***	1.028***
	(0.0128)	(0.0128)
GDP per capita (in logs)	465.2***	471.3***
	(137.9)	(140.3)
Disaster * ln GDP per capita	-438.0**	-478.0**
	(176.0)	(236.6)
Share of Agriculture	11.09	10.84
	(6.888)	(6.951)
Disaster * Agriculture	-83.74	-32.69
	(54.16)	(116.7)
Polity2	5.362	5.330
	(6.361)	(6.369)
Observations	2,268	2,268
R-squared	0.970	0.970
Number of Countries	104	104

Notes: “indexla” disaster index, sum of types weighted by land area and “disindexla” disaster index, sum of types weighted by inverse of standard deviations and by land area. Annual data 1979-2010, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.9: Alternative estimation methods with baseline specification

	Dependent variable: Credit per capita			
	(1)	(2)	(3)	(4)
	Fixed Effects	OLS	System GMM	Driscoll-Kraay standard errors
Disaster (% Pop. Affected)	35.35**	64.27***	112.5**	35.35***
	(14.08)	(16.87)	(55.59)	(11.26)
Lagged Credit per capita	1.000***	1.027***	0.960***	1.000***
	(0.0172)	(0.00714)	(0.0196)	(0.0392)
GDP per capita (in logs)	654.0***	229.2***	545.9***	654.0***
	(176.3)	(53.77)	(178.0)	(224.2)
Disaster * ln GDP per capita	-4.669**	-8.013***	-15.22**	-4.669***
	(1.807)	(2.019)	(7.083)	(1.512)
Share of Agriculture	15.64**	13.35***	24.84***	15.64**
	(7.006)	(3.588)	(8.168)	(6.289)
Disaster * Agriculture	-0.135*	-0.341***	-0.449	-0.135**
	(0.0763)	(0.113)	(0.475)	(0.0534)
Polity2	-1.064	6.394**	28.89**	-1.064
	(5.273)	(2.698)	(12.14)	(6.811)
Observations	3,189	3,189	3,189	3,189
R-squared	0.958	0.992		0.958
Number of Countries	147		147	147
Number of Instruments			66	
Arellano-Bond Test AR(1)			0.278	
Arellano-Bond Test AR(2)			0.053	
Arellano-Bond Test AR(3)			0.156	
Arellano-Bond Test AR(4)			0.283	
Hansen Test			0.817	

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Columns 1-3 robust standard errors in parentheses. Column 4 Driscoll-Kraay standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 No. of lags used to instrument the endogenous disaster variables in system GMM regression limited to 10 starting at lag 3.

2.4.8 Purchasing Power Parity

All results above use market exchange rates. This may be misleading as this unit of measurement does not accurately reflect standards of living. Therefore, we repeat our exercise using per capita credit and GDP measured in purchasing power parity (PPP) constant 2005 US$ by employing output-based real GDP data from the Penn World Tables Version 8.0. We also apply logarithmic transformation to our credit variable. Table A.11 in the Appendix shows the results, which are consistent with those above.

2.4.9 Cross-sectional Dependence and Geographical Regions

Given that there might be cross-sectional dependence in disaster data due to spatial nature of disasters, we use Driscoll and Kraay (1998) errors to overcome any such issue (Column 4 of Table 2.9). Yielded coefficients are precisely identical to the base model's coefficients suggesting that our analysis does not suffer from cross-sectional dependence.

Splitting the sample by region, we get consistent results only for Asia and East Asia & Pacific. See Table A.12 and Table A.13 in the Appendix.

2.4.10 Disaster Subgroups

The impact of all disasters is dominated by climatic and meteorological disasters (in EM-DAT's classification). See Table A.14 in the Appendix.

We run our baseline specification for different disaster subgroups. As expected from the descriptive statistics, results for climatic disasters are very similar to the results for all disasters. Our main findings also hold for biological and geophysical disasters. However, although we get the same signs above for the variables of interest for hydrological disasters, results are insignificant for hydrological and meteorological disasters. See Table A.15 in the Appendix.

As one can argue that biological disasters are completely different from other disasters, we re-estimate our baseline specification across alternative estimators after dropping biological disasters. As apparent from Table A.16 in the Appendix, results are very similar to the original.

2.4.11 Binary Disaster Variable

Following McDermott et al. (2014), we run our baseline fixed effects estimator using a binary disaster variable, which is zero for disasters that below a threshold and one for disasters above. This restricts the variable of interest to the presence or absence of a disaster in a given country year, ignoring for the magnitude of the disaster. By doing this we reduce potential endogeneity, as it is unlikely that credit could control the occurrence of disasters. The binary disaster variable of course contains much less information than the continuous one.

We use different thresholds to identify severe disasters. The results are consistent results with the above with respect to the sign regardless of the threshold. Effects become significant for thresholds of 5.5% or higher. See Table A.17 in the Appendix. Without the disaster-agriculture interaction, which is never significant, disasters and the income-disaster interaction are significant at a 1% threshold. See Table A.18 in the Appendix.

2.4.12 Impact Disaster Variable

We construct a disaster impact dummy variable following Fomby et al. (2013). These do not yield results consistent with our baseline specification. However, when the model includes only impact variable, lagged credit and logged GDP per capita as controls, the sign on the coefficient of impact variable is consistent. See Table A.19 and Table A.20 in the Appendix.

2.4.13 Weighed Disaster Variable

Following (Noy, 2009) we weigh our disaster measure in terms of the onset month. With weighed disaster data we do not get significant results but signs on the coefficients are consistent with those above. It is to be noted that by using formula $Weighed\ Disaster = Disaster * (12 - Onset\ Month)/12$ for each disaster event, we remove data on a substantial number of events which occurred in the month of December, and EM-DAT does not report onset month for more than 100 events. See Table A.21 in the Appendix.

2.4.14 Causality

The use of binary variable does not completely rule out any potential feedback or reverse causality. To ensure that we disentangle real causality of current disasters on current credit, we carry out a simple test. We repeat our baseline analysis with disasters occurred in subsequent years. A disaster that occurs in a future year cannot affect annual credit of the current year. As such, we do not expect to observe a significant impact of disaster leads on contemporaneous credit.

Table 2.10 shows the results of this exercise. Disasters occur in the following year (Column 2) and the second year (Column 3) do not show a significant impact on current credit supporting our original findings.

Table 2.10: Use of disaster leads with baseline specification

	Dependent variable: Credit per capita		
	(1)	(2)	(3)
	Baseline	F.Disaster	F2.Disaster
Disaster (% Population Affected)	35.35**	24.55	-2.254
	(14.08)	(14.99)	(15.65)
Lagged Credit per capita	1.000***	1.016***	1.047***
	(0.0172)	(0.0146)	(0.00930)
GDP per capita (in logs)	654.0***	517.0***	310.9***
	(176.3)	(142.5)	(99.03)
Disaster * ln GDP per capita	-4.669**	-3.470*	0.0568
	(1.807)	(1.801)	(1.945)
Share of Agriculture	15.64**	12.62**	8.278
	(7.006)	(6.250)	(5.081)
Disaster * Agriculture	-0.135*	-0.0717	0.0415
	(0.0763)	(0.130)	(0.122)
Polity2	-1.064	0.381	4.546
	(5.273)	(4.858)	(4.189)
Observations	3,189	3,076	2,958
R-squared	0.958	0.959	0.961
Number of Countries	147	146	143

Notes: Annual data 1979-2011, except where first observation lost due to lags and leads. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

2.5 Alternative Measures of Financial Development

Private credit represents only the depth of financial institutions. Using our baseline model and the fixed effects estimator, we consider alternative indicators of financial development. We cannot use all measures suggested by Čihák et al. (2013) because of an insufficient number of observations. Most of these data are available only from 2000 or 2003 onwards.

It is not possible in any manner to plug all the different measures of financial development in our model as they are, given their nature and measurement units. To see the impact of natural disasters on various financial development indicators, it is necessary to employ proper estimation strategies on relevant variables for appropriate sub-samples with respect to space and time. For instance, exploring disaster effects on bank solvency, Klomp (2014) limits his sample to highest economic damage causing 170 severe disasters and time period from 1995 to 2010 in quantifying the impact of natural disasters on banks' distance to default.

Thus, it is obvious that all the indicators of financial development would not give rise to consistent results in our model. Nevertheless, as apparent from Table A.22 in the Appendix, we find strongly consistent results for liquid assets to deposits and short term funding (%) which represents financial stability.

This indicator is the ratio of the value of the liquid assets of banks which can be easily convertible to cash, to their total deposits and short term borrowings. Higher value for this ratio represents higher liquidity and financial stability as banks are in a position to meet their immediate financial obligations without trouble. As in the case for private credit, natural disasters significantly increase the liquidity of banks reflecting their ability to meet disaster affected parties' immediate need for finances. However, higher per capita income moderates this effect as it lessens the need for borrowing.

As apparent from Table A.23 – Table A.26 in the Appendix, some other financial indicators too yield consistent results at least with respect to the signs on the coefficients of the variables of interest.

Table A.23 contains regression results with respect to disaster variable and its interaction with income on other indicators which represent financial depth. Financial depth is not a financial function itself but a proxy to reflect the magnitude of overall services extended by the financial system (Čihák et al., 2012, p. 8). Deposit money bank's assets as percentage of GDP (gfdd_di_02) appears to increase with contemporaneous disasters but decrease when income is high. This is obvious as credit disbursed by banks constitutes part of banks' assets. Nonetheless, this is not true when it comes to assets of non-bank financial institutions (gfdd_di_03) that do not accept transferable (demand) deposits as apparent from negative sign on the disaster coefficient. Natural disasters seem to increase demand, time and saving deposits in deposit money banks and other financial institutions as a share of GDP (gfdd_di_08). This can be the case as banks can attract more deposits by offering a higher interest rate to finance their disaster related credit which can be offered at even higher rate to desperate parties at the receiving end. Volumes of life and non-life insurance premium (gfdd_di_09 and gfdd_di_10) are reduced by natural disasters. Insurers may be reluctant to accept risks in the presence of contemporaneous disasters. Further, it is to be noted that insurance penetration is lower in poor countries which are more prone to disasters. Stock market capitalisation as represented by total value of all listed shares in a stock market exchange as a percentage of GDP (gfdd_dm_01) tends to decrease with natural disasters indicating adverse impact of such events on corporate sector. Nevertheless, increased total value of all traded shares in a stock market exchange as a percentage of GDP (gfdd_dm_02) due to natural disasters may be an indicator of shareholders' attempt to recover financial needs through disposal of shares, or reflect investors' worries about profits and dividends. Outstanding domestic private and public debt securities as a percentage to GDP (gfdd_dm_03 and gfdd_dm_04) significantly decrease with natural disasters and more so when the income is low. Bond holders may be resorting to early redemption to finance disaster recovery as and when needed. A puttable bond vests the right upon holder to force the issuer to repay the bond prematurely. Total value of outstanding international debt issues both public and private, as a share of GDP (gfdd_dm_07) would be likely to decline as the credit rating of a country rapidly deteriorate after a natural disaster.

When financial access is considered, number of bank accounts per 1,000 adults (gfdd_ai_01) and number of commercial bank branches per 100,000 adults (gfdd_ai_02) tend to rise in the presence of natural disasters (see Table A.24). This reflects the positive response from both demand and supply side after a natural disaster as financial inclusion should be expanded to reach disaster recovery related financial requirements. In line with the impact of natural disasters on stock market as mentioned afore value of all traded shares outside of the largest ten traded companies as a share of total value of all traded shares in a stock market exchange (gfdd_am_01) tend to increase whilst value of listed shares outside of the ten largest companies to the total value of all listed shares (gfdd_am_02) tend to decrease with natural disasters owing to similar reasoning. Total amount of domestic non-financial corporate bonds and notes outstanding to total amount of domestic bonds and notes outstanding, both corporate and non-corporate (gfdd_am_03) seems to increase with disasters, maybe highlighting the active role played by the corporate sector over the non-corporate sector by raising liquid funds to finance disaster recoveries.

Regression results of indicators for financial efficiency are summarised in Table A.25. We observe an increase in the accounting value of bank's net interest revenue as a share of its average interest bearing assets (gfdd_ei_01), the difference between lending rate charge by banks on loans to the private sector and the deposit interest rate offered by commercial banks on deposits with three-month tenure (gfdd_ei_02) and bank's income that has been generated by non-interest related activities such as trading gains, fees, commissions and other operating income as a percentage of total income (gfdd_ei_03) because increased disaster related credit raises interest income, interest differential as well as fees, commission and other activity income including valuation and evaluation income. Operating expenses of a bank as a share of the all assets held (gfdd_ei_04) decreases as it can be assumed that banks operate with existing administrative resources in handling higher demand for disaster related credit whilst increased credit expands the asset base. Maybe for the same reason, commercial banks' after-tax net income to yearly averaged total assets (gfdd_ei_05) appears to decline. However, as natural disasters do not necessarily increase equity of banks in the manner they increase interest and other income, commercial banks' after-tax net income to yearly averaged equity (gfdd_ei_06) increases. Since this impact does not depend on income tax, we observe a similar reaction with respect to commercial banks' pre-tax income to yearly averaged total assets (gfdd_ei_09) and commercial banks' pre-tax income to yearly average equity (gfdd_ei_10). Total value of shares during the period divided by the average market capitalisation for the period (gfdd_em_01) increases, maybe due to increased trading and reduced capitalisation, as stated earlier.

When it comes to financial stability (see Table A.26), bank Z-score which captures the distance to default of a country's commercial banking system (gfdd_si_01) decreases with disasters. Following Klomp (2014), we take the logarithm of this ratio of return-on-assets plus equity-asset ratio to standard deviation of return-on-assets. Supporting his findings we also see that disasters increase the likelihood of bank defaults weakening financial system stability. Ratio of gross value of defaulting loans (repayments of interest and principal past due by 90 days or more) to gross loans (gfdd_si_02) also reduces with disasters characterising a healthy financial system. Ratio of bank capital and reserves to total financial and non-financial assets (gfdd_si_03) increases with natural disasters. It is puzzling as to why the financial resources provided to the private sector by domestic money banks as a share of total deposits (gfdd_si_04) decline when we observe an increase in the private credit. Maybe banks attracting more deposits than the disbursed credit as now they are in a position to offer a higher deposit interest rate. The ratio of total bank regulatory capital to its assets held, weighted according to risk of those assets (gfdd_si_05) increases with disasters. Again it is surprising that the provisions to non-performing loans (gfdd_si_07) increase in a scenario of observable decline in non-performing loans. It is rational to see an increase in stock price volatility (gfdd_sm_01) i.e., the average of the 360-day volatility of the national stock market index as natural disasters unambiguously create an uncertainty in the stock market in the short run.

2.6 Conclusion

This paper shows that natural disasters have a significant positive impact on financial development, more specifically on the per capita private credit disbursed by domestic banks. This effect is dampened by higher per capita income. The positive impact of natural disasters on private credit is further mitigated by higher agricultural dependency of the economy. In other words, we find strong evidence that companies and households get deeper into debt after a natural disaster. This effect is stronger in poorer countries. We find some evidence that suggests that the effect is weaker in countries where agriculture is more important.

Nominal change in per capita credit due to an increase in the disaster measure diminishes with higher income. As the percentage of population affected by disasters increases, poor countries with lower per capita income will see an increase in their nominal per capita credit, however, rich countries with higher per capita income will experience a decline in their nominal per capita credit. Nevertheless, given that the magnitude of the per capita credit countries already enjoy differs considerably across countries irrespective of their per capita income, the real impact on credit relies upon the prevailing per capita credit. So, we would conclude that the impact of natural disasters on financial development proxied by credit is country specific as well as time specific.

Our findings are robust to various checks. We get consistent results when we include controls which represent macroeconomic stability, government spending, and trade openness enhancing our baseline specification. Once we control for other relevant factors such as non-life insurance penetration, financial sector regulation, lending interest rate, resource rent and foreign aid while employing baseline model and its slight variants, we yet observe consistent results. Our findings are also robust to alternative estimators. We take various measures to rule out any potential endogeneity issue including the use of system GMM estimator and binary disaster variable. Further, using the ifo GAME disaster data we again find a positive impact of disasters on private credit mitigated by higher income, supporting our original findings. Furthermore, we consider alternative indicators of financial development, and find that, qualitatively, our results carry over.

Private credit is only one dimension of financial development, but our results for other indicators suggest that natural disasters have a broader impact on financial development. Further, as poor countries are more vulnerable to disasters and their financial markets are less well developed, the role played by formal credit in disaster consequences would be small. The immediate impact of natural disasters is better interpreted as households getting (further) into debt rather than as financial development, but we find longer term impacts too that indicate an expansion of credit availability.

With our findings, we hope that relevant policy makers in disaster vulnerable countries would take well informed and well thought decisions with respect to financial inclusion, domestic bank lending, direct credit and related matters in order to enhance financial development.

Any research comes with caveats which should be explored in further analysis. Two stand out. First, we use nationally aggregate data. Changes at the aggregate level are open to misinterpretation and may obscure the actual mechanisms. The analysis here should therefore be repeated with microdata. Second, we find that natural disasters affect financial development. Earlier papers found that financial development affects vulnerability to natural disasters. Our analysis should therefore be repeated with a dynamic model of simultaneous equations. These issues are deferred to future research.

3 Foreign Aid Concentration and Natural Disasters

3.1 Introduction

Natural disasters attract foreign aid. The focus of this paper is the impact of natural disasters on the aid concentration of recipient countries. The paper shows that natural disasters lead to a diversification of aid received, in terms of both the number of donors contributing and the types of aid received. This is true in the immediate aftermath of the disaster, and continues long after. The literature on the fragmentation of aid shows that, typically, aid is less effective in promoting economic development when it comes from many sources and is spread over many programmes (Gehring, Michaelowa, Dreher, & Spörri, 2017; Kimura, Mori, & Sawada, 2012; Oh & Kim, 2015; Sumner & Glennie, 2015). The paper thus shows that, besides the negative effect of natural disasters on economic growth, natural disasters also have a negative impact on development aid. As far as we know, no one has explored the impact of natural disasters on aid concentration of aid recipient countries with respect to their aid portfolio/donor base before, thus, this study allows us to bridge a gap present in the current literature.

As Yang (2008) shows disasters increase foreign aid considerably and poorer countries could cover approximately three fourths of disaster damages due to hurricanes through foreign aid from public sources alone. There is a plethora of studies to support the fact that natural disasters increase the magnitude of foreign aid received by affected countries owing to various donor motives (Becerra et al., 2014, 2015; Wei et al., 2014; Wood & Wright, 2016). It is also well established that there is a higher probability for disaster affected countries to receive more foreign aid when the disaster news coverage is wide and when the disaster affected countries have close connections (historical, political, cultural or religious, etc.) with potential donors prior to the disaster (Olsen, Carstensen, & Høyen, 2003; Strömberg, 2007). When disasters occur, the affected countries become the centre of international media attention. This news coverage helps affected countries to reach priority lists of potential foreign aid donors. Disasters create a platform for politicians, activist groups and affected parties to lobby their appeals for aid and to raise awareness of their development needs among potential donor entities. Through this awareness, disasters ultimately become an indirect determinant of donor future allocation decisions. As a result, disasters attract more donors and also aid meant for development purposes other than disaster related matters leading to a reduction in aid concentration in recipient countries.

The existing literature also discusses the determinants of post natural disaster aid allocations across space and time. Specifically, using an event study analysis approach of post disaster aid-surges, Becerra et al. (2014) whilst arguing that aid-surges cover only 3% of the estimated damages due to natural disasters (despite the median increase in ODA by 18% compares to pre disaster flows), identify disaster intensity and country characteristics such as level of development, country size and magnitude of foreign reserves as key determinants of post disaster aid-surges.

It is obvious that natural disasters enhance aid aimed at emergency and disaster relief, and perhaps preparedness too. This aid supposedly facilitates speedy and smooth recovery and reconstruction after natural disasters. There is evidence also to suggest that past foreign aid flows suppress the political willingness to invest on disaster prevention and mitigation intentions (Raschky & Schwindt, 2016). It is also to be noted that Becerra et al. (2015) present some evidence of cross-sectorial substitution where donors sometime decrease aid aimed at other sectors in order to increase humanitarian aid given to the same recipient.

Constructing a Herfindahl-Hirschman index for donor concentration, which acts as a proxy for aid proliferation in recipient countries, Kimura et al. (2012) find that aid proliferation negatively affects economic growth, especially in Africa. As Aldasoro, Nunnenkamp, and Thiele (2010) point out, aid proliferation, donor fragmentation and the lack of coordination have been widely identified as serious problems for aid effectiveness. Oh and Kim (2015) also find that donor proliferation is harmful to the recipient's growth in the long run. Gehring et al. (2017) present evidence to confirm negative effect of fragmentation on aid effectiveness in terms of economic growth. Acharya, De Lima, and Moore (2006) show that aid proliferation and fragmentation cause unacceptably high direct and indirect transaction costs on many recipient countries.

In this paper, we examine the impact of natural disasters on concentration of foreign aid categories and donor base of aid recipient countries. The expansion in aid portfolio materialises through more diversified categories (beyond disaster related categories) under which aid recipients receive charitable receipts. Donor base expands when the number of donor entities from whom a recipient receives donations is increased. The analysis uses a cross country panel data set covering the period from 1979 to 2010. Employed disaster indices are purely based on physical intensities of disasters, thus overcome common issue of endogeneity in natural disaster data. Findings suggest that natural disasters attract not only aid aimed at emergency, disaster relief and preparedness but also foreign aid under multiple other development categories such as education, healthcare, environmental protection, natural recourses, forestry, technology, industry, construction, energy, agriculture, social welfare, water, transportation, trade, political stability and financial development. As such, natural disasters expand recipient aid portfolio with respect to categories under which they receive foreign aid. Not only that, natural disasters increase the number of donors who donate aid to a recipient country reducing recipient's dependence on a single donor. So, this is an expansion in the recipient aid donor base / network in terms of number of donors. Further, natural disasters also reduce aid concentration with respect to aid categories and donors as measured by the Herfindahl-Hirschman index.

The rest of the paper proceeds as follows. Section 2 introduces data and the empirical methodology. Section 3 discusses results followed by robustness checks in section 4. Concluding section 5 discusses findings and policy implications of the study. It also points out limitations of the paper whilst suggesting potential avenues for further research in the future.

3.2 Empirical Analysis

3.2.1 Data

The source of foreign aid data for this study is the international aid data provided by AidData's Research Release 2.1 (Tierney et al., 2011). AidData is a project of the partnership among Brigham Young University, the College of William and Mary, and Development Gateway. "AidData defines development finance to include not only traditional Official Development Assistance (ODA) but also loans or grants from governments, official government aid agencies, and inter-governmental organisations intended mainly to promote the economic development and welfare (broadly defined) of developing countries…" (Tierney et al., 2011, p. 1892). However, AidData does not include funding from nongovernmental organisations, private investors, banks or foundations and military assistance. AidData covers information on development finance activities from 1946 - 2013. Aid Data has augmented the OECD Creditor Reporting System (CRS) database with more data gathered from donor annual reports, project documents from both bilateral and multilateral aid agencies, donor agency sources, and agency websites and databases.

The amount of aid used in this analysis is the commitment amount (in constant 2009 USD) the donor (donor country or the multilateral organisation) has agreed to provide for the duration of the project, often disbursed over the following years. AidData has developed a five digit coding system to identify the sector and purpose of the project. We use these codes to classify aid categories.

Other economic indicators and natural disaster data are taken from the ifo GAME data (Felbermayr & Gröschl, 2014). Natural disaster data are generally subject to criticism over the potential endogeneity issues as measures of natural disaster outcomes are often affected by socio and economic conditions of affected areas. Natural disaster data of ifo GAME data are unique in the sense that they have been constructed purely based on the physical intensities of disasters so that the measures have entirely overcome the endogeneity problem.

The ifo GAME data presents two aggregated natural disaster indices, namely ‘disindexla’ (disaster index 1) and ‘indexla’ (disaster index 2). To compile these disaster indices physical intensity data of earthquakes, volcanic eruptions, storms, floods, droughts and extreme temperature events have been extracted from primary geophysical and meteorological databases. The physical intensity measure used for earthquakes is the maximum realisation value on the Richter scale within a single earthquake episode. The highest recorded Volcanic Explosivity Index (VEI) during a volcanic eruption has been used for volcanic intensity. The maximum total wind speed in knots on a country basis reflects storm intensity. Floods are measured as the positive difference in total monthly precipitation whilst droughts take value unity in an indicator variable if the rainfall is below 50% of the long-run monthly mean at least for three consecutive months or five months within a year, and zero otherwise (Felbermayr & Gröschl, 2014, pp. 94-95). All the disaster measures are aggregated into an overall composite disaster index.

Composite disaster indices, ‘indexla’ and ‘disindexla’ are the sum of physical intensity measures of different types of disasters occurred in a given country in a given year. Both indices are weighted by log area of that country appreciating the fact that economic effects of disasters vary with the extent of a country. ‘Disindexla’ is further weighted by respective inverse sample standard deviations. Use of the inverse of the standard deviation of a disaster type within a country over all years rules out the dominance movement of disaster index by any single disaster component (Felbermayr & Gröschl, 2014, p. 98).

Disaster index 'indexla' is created using an unweighted sum of disaster intensity measure after scaling for all respective disaster variables by land area. However, 'disindexla' further uses the inverse of the standard deviation of a disaster type within a country over all years as precision weights. Therefore, no single disaster component dominates the movement of the disaster index, 'disindexla'. For this reason, 'disindexla' appears to be a better index to represent natural disasters over 'indexla'. As such, more refined disaster index, 'disindexla' is used in this analysis.

In our analysis, the Herfindahl-Hirschman index (HHI) (Hirschman, 1964) is employed to measure foreign aid concentration. The index which uses following formula varies between 0 and 1.

$$HHI_{it} = \sum_{j=1}^{N} S_j^2 \qquad (3.1)$$

where HHI is the Herfindahl-Hirschman index which measures aid concentration in country *i* for year *t*, S_j is the share of donations received under category *j* or from donor *j*, and *N* is the number of categories or donors. An index value of one for the *HHI* which is constructed based on categories under which foreign aid is received by recipient countries ($HHI^{categories}$), represents a perfectly concentrated aid portfolio where the recipient receives entire foreign aid under one category. An index value close to zero represents an extremely diversified aid portfolio where the recipient receives a good spread of foreign aid under many more categories.

An index value of one for the Herfindahl-Hirschman index which is constructed based on donors from whom recipients receive foreign aid (HHI^{donors}) indicates a perfectly concentrated aid network where all the aid is received from the same donor. A value close to zero indicates donor diversification where single donor dependence is much less.

Table 3.1: Summary statistics (post estimation)

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Herfindahl-Hirschman Index, Aid Cat. (*HHI* ^{categories})	2,425	0.2804	0.2031	0.0794	1
Herfindahl-Hirschman Index for Donors (*HHI* ^{donors})	2,183	0.3176	0.2302	0.0606	1
Disaster Index 1 (disindexla)	2,425	0.0317	0.1756	6.63e-06	2.228
Disaster Index 2 (indexla)	2,425	0.0323	0.1745	1.06E-06	2.155
GDP per capita, PPP (in logs)	2,183	7.847	1.127	5.491	11.238
Polity Index of Polity IV Project	2,183	0.582	0.333	0	1
Domestic Credit by Banking Sector (% of GDP)	2,183	0.460	0.377	-0.730	2.489
Current Account Balance (% of GDP)	2,183	-0.031	0.081	-0.448	0.446
Population (in logs)	2,183	9.485	1.456	6.915	14.096
No. of Aid Categories	2,183	14	4	1	18
No. of Donors	2,183	19	10	1	47
Total Amount, Aid Received (in constant 2009 US$)	2,425	1.53E+09	3.00E+09	1811.3	5.87E+10

Post estimation summary statistics for the variables used in the analysis are shown in Table 3.1. On average, Herfindahl-Hirschman index for aid categories (*HHI* ^{categories}) is around 0.28 and Herfindahl-Hirschman index for donors (*HHI* ^{donors}) is around 0.32 reflecting a moderately concentrated foreign aid portfolio / network. Disaster indices, ‘disindexla’ and ‘indexla’ take mean values of 0.0317 and 0.0323, respectively. Summary statistics of disaster indices ‘disindexla’ and ‘indexla’ are very similar. The reason for this is that these measures have been further scaled so that they admit the same mean to facilitate comparison (Felbermayr & Gröschl, 2014, p. 98). Countries receive aid from 19 donor entities on average in a country year. The minimum number of donors per country is 1 whilst the maximum number can be as high as 47. Meanwhile, they receive aid under 14 different categories, on average and the number of categories can vary between 1 and 18. These eighteen categories are emergency and disaster relief and preparedness; environmental protection; mining, metals and mineral resources; forestry; technology;

industry; construction, real estate and urban planning; healthcare; education; energy; agriculture, livestock, food and fishing; social welfare; water; transportation; trade, economic and business policy; political; financial; and unclassifiable.

Figure 3.1 presents the variation of average aid per capita and average Herfindahl-Hirschman index for aid categories ($HHI^{categories}$) across countries. Figure 3.2 shows the variation of aid concentration measured by Herfindahl-Hirschman index for aid categories ($HHI^{categories}$) by countries over time.

Figure 3.1: Variation of aid across countries

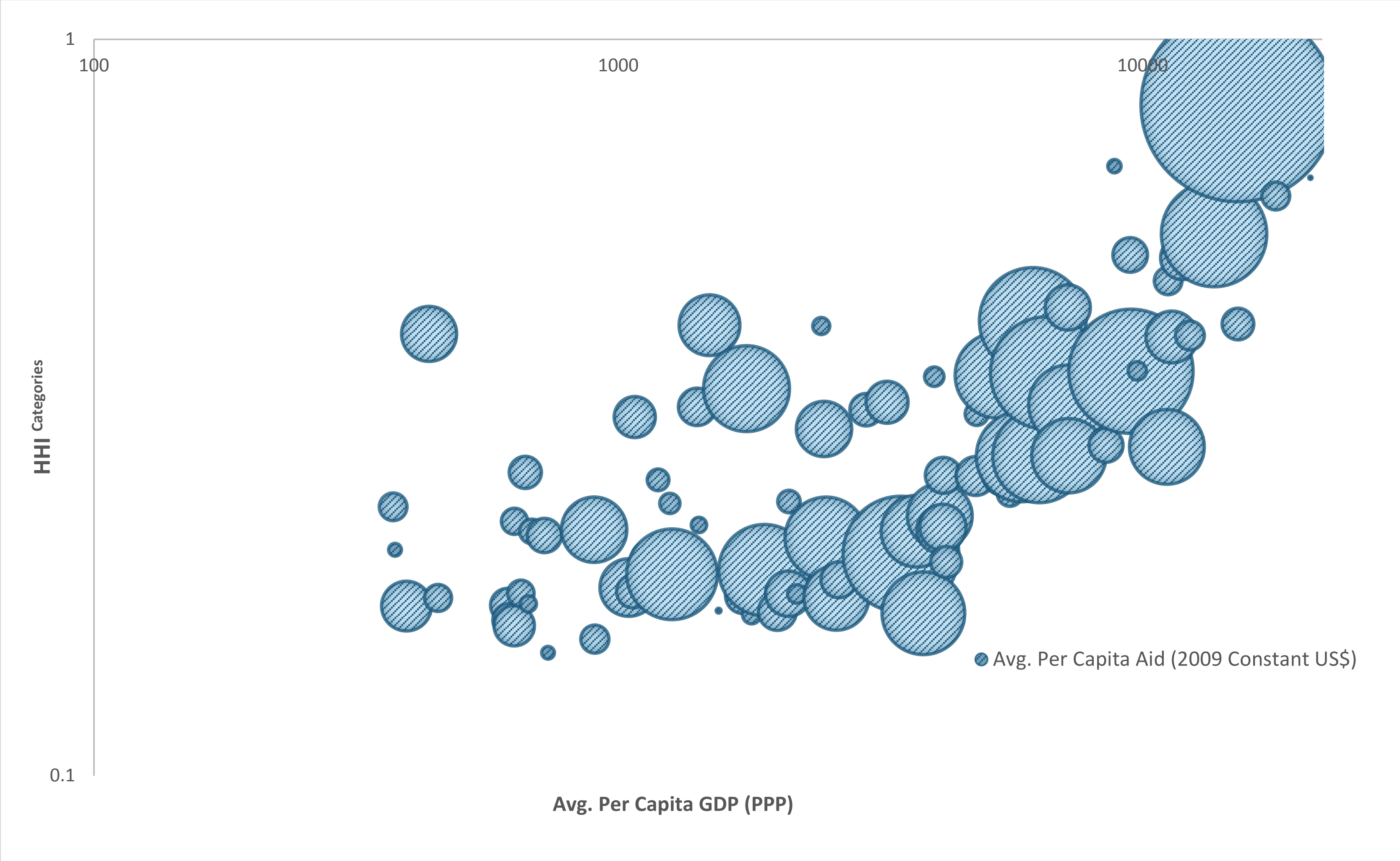


Figure 3.2: Variation of aid concentration measured by Herfindahl-Hirschman index for aid categories ($HHI^{categories}$) by countries over time

AGO	Angola
ALB	Albania
ARG	Argentina
ARM	Armenia
AUS	Australia
AZE	Azerbaijan
BDI	Burundi
BEL	Belgium
BFA	Burkina Faso
BGD	Bangladesh
BGR	Bulgaria
BLR	Belarus
BOL	Bolivia
BRA	Brazil
BWA	Botswana
CAN	Canada
CHE	Switzerland
CHN	China
CIV	Cote D'Ivoire
CMR	Cameroon
COG	Congo, Rep.
COL	Colombia
CRI	Costa Rica
CZE	Czech Republic
DEU	Germany
DNK	Denmark
DOM	Dominican Republic
DZA	Algeria
ECU	Ecuador
EGY	Egypt
ESP	Spain
ETH	Ethiopia
FIN	Finland
FRA	France
GAB	Gabon
GBR	United Kingdom
GRC	Greece
GTM	Guatemala
HND	Honduras
HRV	Croatia
HTI	Haiti
HUN	Hungary
IDN	Indonesia
IND	India
IRL	Ireland
ISR	Israel
JOR	Jordan
JPN	Japan
KEN	Kenya
KGZ	Kyrgyz Republic
KOR	Korea
KWT	Kuwait
LAO	Laos
LBR	Liberia
LKA	Sri Lanka
MAR	Morocco
MDG	Madagascar
MEX	Mexico
MKD	Macedonia, FYR
MLI	Mali
MNG	Mongolia
MOZ	Mozambique
MRT	Mauritania
MYS	Malaysia
NAM	Namibia
NER	Niger
NIC	Nicaragua
NLD	Netherlands
NOR	Norway
NPL	Nepal
NZL	New Zealand
OMN	Oman
PAK	Pakistan
PAN	Panama
PER	Peru
PHL	Philippines
PNG	Papua New Guinea
POL	Poland
PRT	Portugal
PRY	Paraguay
ROM	Romania
RUS	Russia
RWA	Rwanda
SEN	Senegal
SGP	Singapore
SLV	El Salvador
SRB	Serbia
SVK	Slovak Republic
SVN	Slovenia
SYR	Syria
TCD	Chad
TGO	Togo
THA	Thailand
TJK	Tajikistan
TTO	Trinidad & Tobago
TUN	Tunisia
TZA	Tanzania
UGA	Uganda
UKR	Ukraine
URY	Uruguay
USA	United States
VNM	Vietnam
YEM	Yemen
ZAF	South Africa
ZMB	Zambia

3.2.2 Empirical Model

We employ a panel regression estimator with country and year fixed effects as the main estimation tool in our analysis. The fixed effects estimator with time dummies takes care of country specific characteristics that do not change over time (unobservable heterogeneity) and time-variant shocks common to all countries.

The panel regression equation of the most parsimonious model is as follows;

$$AidConcentration_{it} = \beta_0 + \beta_1 Dis_{i,t-1} + \theta_i + \theta_t + \varepsilon_{it} \qquad (3.2)$$

where AidConcentration, the foreign aid concentration as measured by Herfindahl-Hirschman index in country *i* for year *t*, is the dependent variable. This measure is based on the categories under which recipient countries receive foreign aid. *Dis* is our disaster index, 'disindexla' taken from the ifo GAME database. It is the sum of physical intensity measures of all natural disasters occurred in a specific country in a specific year weighted by land area of the affected country and respective sample standard deviations. This disaster measure is purely based on physical strengths of disasters. As such, it is expected to rule out in entirety, the potential endogeneity problem of disaster measure being affected by other economic indicators of the affected country.

It takes time for natural disasters to attract foreign aid, specifically aid aimed at other development categories rather than disaster related purposes. Further, disasters can occur at any time of the calendar year. Having considered these, lagged disaster index is included in the equation instead of the contemporaneous disaster index.

Terms θ_i and θ_t are the country and year fixed effects included in the model, respectively. The final term ε_{it} in the equation is the error term. As natural disasters are not evenly distributed across countries, robust standard errors are clustered at country level. However, when clustered even at regional level considering potential spatial dependence, results do not change.

3.3 Results

Results of the baseline model are given in Table 3.2. We find statistically significant negative impact of natural disasters that occurred in the previous year on the recipient foreign aid category concentration as measured by Herfindahl-Hirschman index. Disaster index1, disindexla is the sum of physical intensity measures of disasters took place in a specific country year weighted by the land area of that country and by respective inverse sample standard deviations.

Table 3.2: Results for regressing foreign aid concentration on natural disasters: Base model

	Dependent variable: Aid concentration ($HHI^{categories}$)
	Fixed Effects
Lagged Disaster Index 1 (disindexla)	-0.237***
	(0.0498)
Observations	2,425
Number of Countries	95
R-squared	0.032

Notes: Annual data 1979-2010, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Following Felbermayr and Gröschl (2014), we quantify the marginal aid concentration impact of disasters at different intensities. According to the results, in a year in which the disaster index is equal to the sample mean of 0.0317, aid concentration as measured by Herfindahl-Hirschman index is lower by about 0.0075 index points[5]; a one standard deviation increase of disaster index above the mean reduces aid concentration by about 0.0491 Herfindahl-Hirschman index points[6]. Hence, with disasters, the categories under which countries receive foreign aid would expand reducing aid concentration. It is

[5] -0.237*0.0317

[6] -0.237*(0.0317+0.1756)

obvious that disasters have a positive impact on disaster related aid as disasters attract aid aimed at disaster-connected matters. However, it appears that disasters increase not only disaster related aid but also other kinds of charitable receipts which would in turn affect the economic development of the recipient-country as per the existing literature.

3.4 Robustness Checks

3.4.1 Without "Emergency and disaster relief and preparedness" Category

Our aid categories include the aid category related to natural disasters, i.e. "emergency and disaster relief and preparedness" category. To ensure that the results are not driven by this category, we re-estimate our base model with Herfindahl-Hirschman index calculated excluding this category. As apparent from results contained in Table 3.3 which are strongly consistent with of the base model, this exercise does not make any difference to the original findings.

Table 3.3: Results for regressing foreign aid concentration excluding "emergency and disaster relief and preparedness" category on natural disasters: Base model

	Dependent variable: Aid concentration (*HHI* ^{categories}) excluding disaster related aid category
	Fixed Effects
Lagged Disaster Index 1 (disindexla)	-0.237***
	(0.0490)
Observations	2,423
Number of Countries	94
R-squared	0.034

Notes: Annual data 1979-2010, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.4.2 Contemporaneous Disasters and Second Lag of Disasters

We have used lagged disaster variable in our base model for the reasons set out under 'Empirical Model'. As a further robustness check, we include contemporaneous disasters and a further lag of disasters to check how the model performs in the presence of these variables. Results are presented in Table 3.4. The impact of first lag of disasters does not dissipate once contemporaneous disasters and a further lag of disasters are included. Further, we cannot observe a statistically significant impact of contemporaneous disasters on the aid concentration, confirming the lagged effect of disasters on aid concentration.

Table 3.4: Results for regressing foreign aid concentration on natural disasters: Contemporaneous Disasters and Second Lag of Disasters (fixed effects)

	Dependent variable: Aid concentration (*HHI* ^{categories})		
	(1)	(2)	(3)
Disaster Index 1 (disindexla)		-0.0324	0.0649
		(0.0858)	(0.120)
L. Disaster Index 1 (disindexla)	-0.237***	-0.222***	-0.0982**
	(0.0498)	(0.0252)	(0.0391)
L2. Disaster Index 1 (disindexla)			-0.391***
			(0.108)
Observations	2,425	2,425	2,315
R-squared	0.032	0.032	0.034
Number of Countries	95	95	92

Notes: Annual data 1979-2010, except where observations lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.4.3 Additional Controls

We gradually add more control variables to our very parsimonious base model to check the sensitivity of results. Control variables are added sequentially for easy perusal of their effect. As we can imagine income level as a determinant of aid concentration, we add logged gross domestic product (GDP) per capita (measured in constant purchasing power parity dollars) to the regression. As the political regime of a country plays a role in the aid attracted by that country, acknowledging that most foreign aid is politically influenced, the Polity index of Polity IV Project is added to the regression. As domestic credit disbursed by banking sector as a percentage of GDP indicates the availability of recovery finances and also the level of financial development of the country, credit variable is included in the regression. The dummy variable to the effect whether the country is a member country of OECD also reflects the close ties it has with big donors. Current account balance as percentage of GDP and population variables are also included in the regression equation as additional controls. Considering the time lag it takes for the influence of these controls to be fed into aid concentration, lagged terms of control variables are included in the regression.

As apparent from Table 3.5, the earlier results hold in the presence of other control variables, namely, per capita income, polity, domestic credit availability, being an OECD country, current account balance and population. So, even in the presence of these controls, disasters diversify aid with respect to aid categories.

3.4.4 Alternative Estimators

As a further robustness check, we re-estimate the model with controls using ordinary least squares (OLS), difference and system generalised method of moments (GMM) estimators; see Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998) and (Roodman, 2009b). Results are presented in Table 3.6. All the alternative estimators yield statistically significant negative impact of natural disasters on foreign aid concentration.

Table 3.5: Results for regressing foreign aid concentration on natural disasters: Controls (fixed effects)

	Dependent variable: Aid concentration (*HHI* ^{categories})					
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Disaster Index 1 (disindexla)	-0.225***	-0.216***	-0.226***	-0.226***	-0.227***	-0.234***
	(0.0544)	(0.0518)	(0.0504)	(0.0505)	(0.0571)	(0.0565)
Lagged GDP per capita (logged)	0.0273	0.0187	0.0411	0.0408	0.0609	0.0522
	(0.0392)	(0.0418)	(0.0385)	(0.0386)	(0.0410)	(0.0424)
Lagged Polity Index		-0.0642	-0.0351	-0.0361	-0.0313	-0.0329
		(0.0386)	(0.0328)	(0.0325)	(0.0330)	(0.0331)
Lagged Credit (% of GDP)			0.0810**	0.0815**	0.0623*	0.0603*
			(0.0345)	(0.0344)	(0.0347)	(0.0342)
Lagged OECD Dummy				0.0127	0.00816	-0.00194
				(0.0511)	(0.0524)	(0.0531)
Lagged Current Account Balance (% of GDP)					-0.100	-0.0961
					(0.0753)	(0.0743)
Lagged Population (in logs)						-0.0585
						(0.0766)
Observations	2,425	2,425	2,282	2,282	2,183	2,183
R-squared	0.033	0.038	0.045	0.046	0.045	0.046
Number of Countries	95	95	94	94	94	94

Notes: Annual data 1979-2010, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Results for regressing aid concentration on natural disasters: Alternative estimators

	Dependent variable: Aid concentration (*HHI* ^{categories})			
	(1)	(2)	(3)	(4)
	FE	OLS	Difference GMM	System GMM
Lagged Disaster Index 1 (disindexla)	-0.234***	-0.234***	-0.430***	-0.355***
	(0.0565)	(0.0577)	(0.103)	(0.126)
Lagged GDP per capita (logged)	0.0522	0.0522	0.0857	0.160
	(0.0424)	(0.0434)	(0.178)	(0.111)
Lagged Polity Index	-0.0329	-0.0329	0.00674	-0.0209
	(0.0331)	(0.0338)	(0.100)	(0.0783)
Lagged Credit (% of GDP)	0.0603*	0.0603*	0.0910	0.218**
	(0.0342)	(0.0350)	(0.0890)	(0.0994)
Lagged OECD Dummy	-0.00194	-0.00194	-0.524	0.740**
	(0.0531)	(0.0543)	(0.333)	(0.365)
Lagged Current Account Balance (% GDP)	-0.0961	-0.0961	0.199	0.174
	(0.0743)	(0.0760)	(0.148)	(0.133)
Lagged Population (in logs)	-0.0585	-0.0585	-0.994***	-0.104
	(0.0766)	(0.0783)	(0.278)	(0.0745)
Observations	2,183	2,183	2,065	2,183
R-squared	0.046	0.544		
Number of Countries	94		92	94
Number of Instruments			85	91
Arellano-Bond test AR(1)			0.000	0.000
Arellano-Bond test AR(2)			0.319	0.134
Hansen Test			0.683	0.551

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 No. of lags used to instrument the endogenous variables in difference and system GMM regressions limited to 10 starting at lag 2.

3.4.5 Alternative Aid Measures

Apart from Herfindahl-Hirschman index, we use other indicators which represent aid diversity as the dependent variable. The results of these models are given in Table 3.7. Natural disasters as measured by disaster index, 'disindexla', have a statistically significant positive impact on the number of aid categories under which recipients receive foreign aid (Column 1 of Table 3.7). This indicates an enhancement in the diversification of the recipient aid portfolios. Natural disasters also significantly increase the number of donor entities donating to a given recipient (Column 2 of Table 3.7). This reflects an enhancement in the diversification across aid sources, i.e., donors. Natural disasters also reduce the dependence of a single donor as reflected by the negative effect of the disaster index on Herfindahl-Hirschman index of donors (Column 3 of Table 3.7). Thus, disasters expand the aid donor network of recipient countries enabling disaster prone countries to attract more aid inflows. When we use total amount of aid received by a recipient (in constant 2009 US$) as the dependent variable, the sign on the yielded coefficient is positive although it is not statistically significant (Column 4 of Table 3.7). However, when we use the other composite disaster index, 'indexla' (a less refined disaster measure as it has not been weighted by the inverse of the respective sample standard deviations, as discussed above) presented by Felbermayr and Gröschl (2014), we can see a statistically significant positive impact of natural disasters on total amount of aid (Column 5 of Table 3.7).

3.4.6 Alternative Disaster Data, EM-DAT International Disaster Database

As a further robustness check, we use a disaster measure calculated using disaster data obtained from EM-DAT, the International Disaster Database (Guha-Sapir et al., 2014) and re-estimate our base model. In this exercise, disasters are measured as the percentage of population affected due to all natural disasters during a country year thus it captures humanitarian motives also for foreign aid allocation by donors apart from disaster intensity. Earlier results hold; see Table 3.8. We repeat the analysis using the EM-DAT disaster measure constructed excluding biological disasters for better comparison with the ifo GAME data disaster indices as these composite physical intensity disaster indices do not include biological disasters. Unreported results are almost identical to the ones in Table 3.8.

Table 3.7: Results for regressing foreign aid concentration and other aid measures on natural disasters: Alternative foreign aid measures (fixed effects)

	Dependent variable: Foreign aid measure				
	(1)	(2)	(3)	(4)	(5)
	No. of Aid Categories	No. of Aid Donors	Aid Concentration (HHI^{donors})	Aid - Total Amount (2009 US$)	Aid - Total Amount (2009 US$)
Lagged Disaster Index 1 (disindexla)	5.391***	9.001***	-0.185***	2.235e+08	
	(0.429)	(1.963)	(0.0500)	(3.368e+08)	
Lagged Disaster Index 2 (indexla)					5.225e+08**
					(2.614e+08)
Observations	2,425	2,425	2,425	2,425	2,425
R-squared	0.330	0.745	0.054	0.037	0.037
Number of Countries	95	95	95	95	95

Notes: Annual data 1979-2010, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.8: Results for regressing foreign aid concentration on natural disasters: Alternative disaster data, EM-DAT (fixed effects)

	Dependent variable: Aid concentration
	HHI ^{categories}
Lagged % of population affected due to all natural disasters	-0.000542*
	(0.000292)
Observations	4,729
R-squared	190
Number of Countries	0.042

Notes: Annual data 1979-2010, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.5 Long-Run Effects

To test whether the impact of natural disasters on aid concentration extends to long run, we repeat our analysis with long differences of independent variables. Accordingly, we regress aid concentration on five year differences of independent variables and thereafter on ten year differences. We observe statistically significant negative impact of disasters on aid concentration on both occasions confirming that the impact is not limited only to short run; see Table 3.9.

Table 3.9: Results for regressing aid concentration on natural disasters: Long differences (fixed effects)

	Dependent variable: Aid concentration (*HHI* ^{categories})	
	(1)	(2)
	5 Years	10 Years
Differenced Disaster Index 1 (disindexla)	-0.167***	-0.410***
	(0.0250)	(0.0471)
Differenced GDP per capita (logged)	-0.0971***	-0.0390
	(0.0346)	(0.0340)
Differenced Polity Index	-0.0234	-0.0436*
	(0.0279)	(0.0234)
Differenced Credit (% of GDP)	0.0455*	0.0551
	(0.0246)	(0.0375)
Differenced OECD Dummy	-0.0950*	-0.196**
	(0.0481)	(0.0900)
Differenced Current Account Balance (% GDP)	0.181***	0.116*
	(0.0617)	(0.0674)
Differenced Population (in logs)	-0.263	-0.130
	(0.162)	(0.136)
Observations	1,784	1,356
R-squared	0.057	0.083
Number of Countries	93	90

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.6 Discussion and Conclusion

We explore the impact of natural disasters on foreign aid concentration of aid recipient countries. The disaster indices used are purely based on physical intensities of disasters, so our study overcomes the common issue of endogeneity in natural disaster data. We find that natural disasters increase the number of development categories under which recipient countries receive charitable receipts. We also find that natural disasters increase the number of donor entities from whom disaster affected countries receive foreign aid. Further, natural disasters reduce foreign aid concentration as measured by Herfindahl-Hirschman index. These results hold in the presence of additional controls such as per capita income, trade openness, political regime, domestic credit, foreign direct investments, etc. Apart from panel fixed effects estimator, alternative estimators, namely, OLS, difference and system GMM also yield consistent results. Results are also robust to alternative aid measures, disaster measures and data. Not only short run effects, our study also finds evidence of long run disaster impact on foreign aid concentration.

It can be expected aid aimed at various development objectives such as education, healthcare, environmental protection, natural recourses, forestry, technology, industry, construction, energy, agriculture, social welfare, water, transportation, trade, political stability and financial development to underpin economic development. Aid recipient countries are generally developing countries and donors are wealthy entities with higher technological advancement. Therefore, it can also be expected that any expansion in the donor base of recipient countries to facilitate the economic development of recipient countries with a supportive and robust external network. However, existing literature has identified aid proliferation as an impediment for economic development in recipient countries mainly due to the huge transaction and administrative costs imposed in recipient country’s government and “inefficiency of the overburdened bureaucracy” (Gehring et al., 2017, p. 322).

Accordingly, natural disasters can indirectly affect the development of countries through reduced aid concentration. Thus, policy makers in disaster vulnerable countries should be aware of the link between natural disasters and aid concentration to take appropriate action to transform a destructive calamity into a constructive development effort.

There is only a limited number of different aid categories and, donors with potential and willingness to donate. In addition, disasters are not evenly distributed across countries. As such, our study may not represent a universal picture. Further, it does not identify the exact mechanisms through which natural disasters influence aid concentration or aid concentration affects economic development. Future research can address these issues.

4 Impact of Natural Disasters on Income Inequality in Sri Lanka

4.1 Introduction

Natural disasters disproportionally affect the poor. It is therefore often assumed that natural disasters increase income inequality. However, as Karim and Noy (2016) point out, there is little research on the impact of natural disasters on income inequality. This paper contributes with a study of Sri Lanka.

In the aftermath of a natural catastrophe, it is essential that affected agents should have access to timely and sufficient finances to ensure a smooth and speedy recovery (Keerthiratne & Tol, 2017). Wealthy individuals are in a better position to meet this financial requirement through self-financing as they can use their savings for reconstruction, they are more likely to have bought insurance to cover any losses, and they have better access to loans and credit. Not only that, the rich are often better prepared for natural disasters as they can financially afford to have precautionary solutions to avoid or mitigate disaster damages. Further, the poor are more likely to have irregular income, so that every disruption, either due to the disaster directly or dealing with the aftermath, means a loss in income. As such, even within the same country, natural disasters would differently affect rich and poor individuals. Natural disasters may thus negatively affect the level of income of the poor leading to a widened income inequality in society.

Furthermore, disaster affected territories generally suffer economic damages by way of human and physical capital losses which usually cause declines in average incomes. Accordingly, this may lead to spatial disparities in average incomes ultimately increasing income inequality among individuals within the same economy.

As Karim and Noy (2016, p. 4) highlight, it is apparent from the existing literature that "poorer households are more vulnerable and will bear the direct damages of disasters disproportionally at higher levels and as higher shares of their household's income" compared to rich households (Datt & Hoogeveen, 2003; Kim, 2012; Masozera, Bailey, & Kerchner, 2007; Morris et al., 2002; Rodríguez-Oreggia, 2010; Tesliuc & Lindert, 2002; Toya & Skidmore, 2007).

When a disaster strikes, the magnitude of its impact on an economy depends on characteristics of disaster itself and the prevailing conditions and socio-economic status of the affected territory as a whole. It appears that as a result of a similar natural disaster event more vulnerable poor countries suffer to a greater extent as opposed to their well-prepared wealthy counterparts. Quoting the World Bank, McDermott et al. (2014, p. 751) highlight that 97% of deaths related to natural disasters occur in developing countries and poor countries experience extremely high economic losses as a share of gross national product than rich countries due to natural disasters.

Whilst arguing that natural disasters cause human and economic losses irrespective of the level of economic development countries have achieved, Yamamura (2015) employs panel data for 86 countries covering the period from 1970 to 2004 to examine how the occurrence of natural disasters has affected the income inequality, as measured by Gini coefficient. He finds that natural disasters increase income inequality in the short run, however, this is not observable in the long run.

As Karim and Noy (2016, p. 4) suggest "the direct impact of disasters on the poor (in magnitude, and relative to the rich) cannot be answered" fully by merely "examining the cross-country distribution of costs and economic activity…the evidence on the distribution of the direct impact of a disaster within a country on households in various income levels is less well understood" as it clearly depends on country characteristics. As such, country-level research is warranted in this field.

Using the Vietnam Household Living Standard Survey in 2008, Bui et al. (2014) find that natural disasters increased income inequality among households in Vietnam in 2008. When natural disasters occur, households can suffer large losses in assets and income. However, poor may be more vulnerable to loss of income due to their inability to engage in work and the unavoidable sale of income deriving capital assets as a coping strategy. If poorer households are less prepared for disasters; the poor live in disaster prone areas and homes that are more likely to be damaged; and receive earnings mainly from sectors which are more likely to face downturn (e.g., weather dependent traditional agriculture), poor would bear higher income losses and natural disasters could cause greater income inequality.

Investigating the impact of Cyclone Aila in Sundarbans region in Bangladesh in 2009, Abdullah et al. (2016) establish that income inequality decreased after the cyclone. Another very recent paper by Feng et al. (2016) show that household income fell by 14% due to 2008 Sichuan earthquake in China, however, income inequality did not change. These findings may be somewhat surprising on the face of it as one would expect natural disasters to exacerbate income inequality.

At subsistence level, people possess little that can be lost to a natural disaster. Losses for the wealthier groups would be disproportionately greater due to natural disasters. People on a monthly wage would not see their income affected by a disaster, but small business owners would. Unskilled day labourers may find new opportunities in the reconstruction effort. In other words, the impact of natural disasters on income inequality is ambiguous.

Against this background, we study the impact of natural disasters on income inequality in Sri Lanka at district level, as the first study of this nature. We find that natural disasters decrease income inequality among Sri Lankan households in line with the results of the aforesaid two studies on Bangladesh and China. Our data allow us to decompose income sources, so that we better understand the mechanisms.

The paper proceeds as follows. Section 2 describes data and empirical strategy. Results are discussed in Section 3 followed by Section 4 which contains robustness checks. Section 5 sets out concluding remarks with some policy implications and also recognises the limitations of the study.

4.2 Empirical Analysis

4.2.1 Data

Sri Lanka is a lower middle income country. Officially known as the Democratic Socialist Republic of Sri Lanka, it is an island situated in the Indian Ocean just above the equator, bordering a major maritime route, the renowned 'Silk Route' connecting the western and eastern worlds. Sri Lanka is 65,610 km^2 in extent with a population of around 21.2 million. Sri Lanka is divided into 25 administrative districts within 9 provinces. As reported in the latest Annual Report of the Central Bank of Sri Lanka (CBSL, 2016), life expectancy of Sri Lankans is 75 years and they have a higher literacy rate of around 93%. Sri Lanka is ranked 73rd among 188 countries in the Human Development Index. In 2016, Sri Lanka recorded a gross domestic product (GDP) of US$ 81.3 billion and per capita income of US$ 3,835 (at current market prices). In Sri Lanka both unemployment and real growth rates were 4.4%, in 2016. After ending a 30 year long war and terrorism in 2009, the economy of Sri Lanka grew at an average rate of 6.4% during the next five years. Over the years Sri Lanka has developed to a service oriented economy from a traditional agricultural economy. In 2016, 62.5% of GDP was yielded from services sector, whilst manufacturing and agricultural sectors accounted for 29.6% and 7.9 of GDP, respectively.

Natural disaster data are from the Disaster Management Centre of Sri Lanka, which maintains disaster related data in collaboration with 'DesInventar', the Disaster Information Management System of UNISDR, United Nations Office for Disaster Risk Reduction. Income data and other social and economic indicators are obtained from the Household Income and Expenditure Survey (HIES) series conducted by the Department of Census and Statistics of Sri Lanka from 1990 to 2013. There are six waves, i.e.

1990/91, 1995/96, 2002, 2006/07, 2009/10 and 2012/13 where the data are representative at district level. The only wave which covers the entire country is the latest 2012/13 survey. Due to the ongoing civil war at that time, some districts of Northern and Eastern provinces were not covered in earlier waves. Mid-year district population data are taken from the Registrar General's Department of Sri Lanka and the study uses the Consumer Price Index published by the Central Bank of Sri Lanka.

Extracting the data reported in the official website of Disaster Management Centre, we construct a district-wise annual disaster database for Sri Lanka from 1985 to 2013. It contains the number of people affected due to cyclones, droughts, epidemics, floods, gales, heavy rains, landslides, land subsidence, plagues, storms, strong winds, surges, tornados, and tsunami in each district, yearly. According to the database, around 27 million people were affected from natural disasters in Sri Lanka during the period from 1985 to 2013. Of them, 47% and 45% were affected by droughts and floods, respectively. Extreme wind events were responsible for 6% of the population affected whilst 2% were affected due to epidemics. Following Noy (2009), we normalise the number affected by disasters with *lagged* population. Thus, disasters are measured as the percentage of population affected due to all natural disasters in each district during a calendar year.

To explore the impact of natural disasters on income inequality at district level in Sri Lanka, we compute the monthly income of each household in the survey year based on survey data of HIES series. In the calculations, we take into consideration all monetary and non-monetary income derived from all sources. Free State services, such as education and health, the value of which cannot be ascertained easily and exactly, were not included in the income. Accordingly, household income consists of the followings components (Department of Census and Statistics, 2015).

a) Employment income – wages-salaries, allowances (tips, commissions, overtime), bonus and arrears

b) Seasonal agricultural income – paddy, chillies, onions, vegetables, cereals, yams, tobacco

c) Other agricultural income – tea, rubber, coconut, coffee, pepper, betel, banana, fruits, meat, fish, egg, milk, other food, horticulture

d) Non-agricultural income – mining and quarrying, manufacturing, construction, trade, transport, guest house, restaurants, bars, hotels, etc.

e) Cash receipts – such as pensions, disability / relief payments, dividends, rents, interest amounts received from various types of savings, educational grants and scholarships, school food program, current remittances and local and foreign transfers, other income

f) Windfall income – income by chance or *ad hoc* gains such as compensations, lottery wins, loans, sale of assets such as land, house and jewellery, withdrawals from savings and bank deposits, gratuity, provident fund, income received from births, deaths and marriages, receipts from welfare society, *seettu* (an informal savings scheme among households), repayments of loans given, health and medical aid, insurance, foods and other commendations, disaster relief assistance, etc.

g) Food in kind (mostly the estimated values of the household consumed items such as home grown fruits and vegetables)

h) Non-food in kind (includes estimated rental values of owner occupied housing units)

Household monthly income is calculated by aggregating monthly earnings received from all the components and then it is equivalised to take account of differences in household size and composition so that it becomes a representative income. To adjust incomes on the basis of household size and composition, all incomes are expressed as the amount that an adult would require to enjoy the same standard of living. We employ the widely used Organisation for Economic Co-operation and Development (OECD) modified equivalence scale for this purpose. This scale, first proposed by Hagenaars, De Vos, and Asghar Zaidi (1994), assigns a value of 1 to the household head, of 0.5 to each additional adult member and of 0.3 to each child. A caveat is that OECD modified scale takes into account only the age and number of members in a household even though there may be other characteristics which may vary from household to household such as disability or health status of household members that affect the needs and capacities of such households.

Adjusted household monthly income per adult equivalent after accounting for sample weights is used to calculate mean and median household incomes and inequality measures such as Theil index (Theil, 1967), Gini coefficient (Gini, 1936), inter quartile range and inter quintile range for average income for each district for each survey year. Income measures are converted to real terms using Colombo Consumers' Price Index (annual average, base year 2006) for comparison across survey years.

From the HIES 2006/07 onwards, 7 new sections have been introduced to the HIES series to collect almost all other household information that helps to understand the living standards of the households. These new areas are school education, health information, inventory of durable goods, access to infrastructure facilities, household debts and borrowings, information on housing, sanitary and disasters, and land and agriculture holdings (Department of Census and Statistics, 2015, p. 1).

Based on the above, we construct a panel dataset which contains data on household incomes and expenditures, income and expenditure inequalities, natural disasters, etc. for 25 administrative districts in Sri Lanka for six survey time periods. This is an unbalanced panel as the number of districts covered varies between 17 and 25. The only wave which covers the entire country is the latest 2012/13 survey. Due to the ongoing civil war at that time some districts of Northern and Eastern provinces were not covered in other waves.

Table 4.1: Summary statistics

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Theil	117	0.4396	0.3027	0.1675	2.4802
Gini	117	0.4276	0.0614	0.2880	0.7168
Inter Quartile Range (Rs.)	117	5,698	2,108	2,457	12,458
Inter Quintile Range, Avg. Inc. (Rs.)	117	20,688	10,433	8,383	74,676
Mean Household Income (Rs.)	117	8,891	3,388	4,404	20,580
Median Household Income (Rs.)	117	6,228	1,926	3,302	13,409
Q1 Average Income (Rs.)	117	2,075	1,463	- 9,823	5,627
Q2 Average Income (Rs.)	117	4,490	1,386	2,223	9,809
Q3 Average Income (Rs.)	117	6,264	1,945	3,326	13,534
Q4 Average Income (Rs.)	117	8,941	2,951	4,552	19,437
Q5 Average Income (Rs.)	117	22,763	10,929	10,109	77,315
HCI (Head Count Index)	117	19.00	11.56	1.40	56.20
% of Poor Households	100	15.48	11.05	1.10	42.20
Household Size	117	4.23	0.38	3.68	5.13
% of HH without Electrical Items	66	38.17	15.37	4.70	90.60
% of HH without Vehicles	66	38.07	22.20	10.50	90.80
% of HH with No Rooms	65	2.20	1.87	0	9.00
% of HH with No Safe Drinking Water	66	13.17	10.93	0.50	48.60
% of HH with No Toilet	62	4.31	5.02	0.10	24.40
Disaster (% of Pop. Affected)	150	4.7368	13.4126	0	117.6589
Disaster_lag1	150	8.5613	22.1317	0	174.3878
Disaster_lag2	150	11.7633	23.4198	0	128.5260
Disaster_lag3	150	4.0579	8.0361	0	56.1630
Disaster_lag4	149	4.8619	10.9804	0	62.4662
Disaster_lag5	149	10.7272	24.9794	0	174.3878
Biological (% of Pop. Affected)	150	0.1079	0.2629	0	3.1072
Climatic (% of Pop. Affected)	150	2.2285	11.4782	0	117.5446
Geophysical (% of Pop. Affected))	150	0.0137	0.1240	0	1.4415
Hydrological (% of Pop. Affected)	150	2.1009	6.5334	0	52.6214
Meteorological (% of Pop. Affected)	150	0.2859	2.9010	0	35.5536

Summary statistics for the variables used in the analysis are provided in Table 4.1. On average, disasters affect 5% of the population in a district per annum in Sri Lanka and the maximum percentage of population affected by natural disasters in a district can be as high as 118% (due to multiple disasters in a year). Figure 4.1 demonstrates the variation of mean percentage of population affected due to natural disasters across districts in Sri Lanka[7].

District-wise income inequality measured by Theil index is around 0.44 whilst Gini co-efficient is around 0.43. Per adult equivalent real mean household income is Rs. 8,891 (in constant 2006/07 rupees). It is also observed that the income of the richest quintile is more than 10 folds larger compared to the poorest quintile. Average household size is around 4 and about 15% of the households are poor. Around 2% of housing units are basic with no rooms. Around 38% of households do not possess vehicles or electric equipment. Meanwhile, around 13% of households do not have access to safe drinking water and around 4% of households do not have an exclusive toilet.

[7] We used the Stata command spmap by Maurizio Pisati. See https://ideas.repec.org/c/boc/bocode/s456812.html

Figure 4.1: Variation of mean % of population affected due to natural disasters

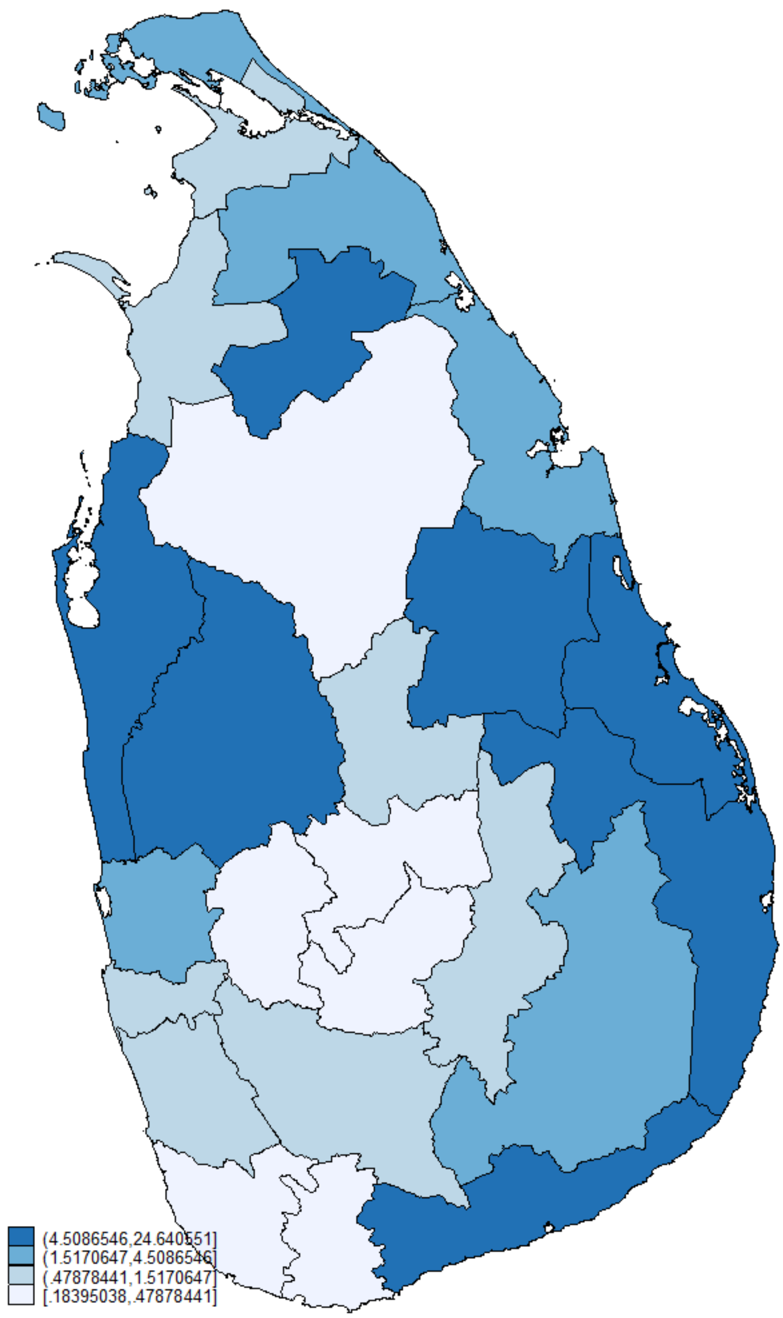


Table 4.2 shows how inequality measures differ by districts. We observe a substantial variation of inequality among districts in Sri Lanka. Kurunegala District records the highest inequality whilst Mannar District records lowest inequality as measured by both Theil index and Gini coefficient. Figure 4.2 and Figure 4.3 demonstrate the variation of mean inequality measured by Theil index across districts in Sri Lanka.

Table 4.2: Mean inequality measures by districts

District	**Theil**	**Gini**	**IQ^4R (Constant 2006 Rs.)**	**IQ^5R, Avg. Income (Constant 2006 Rs.)**
Ampara	0.3788	0.4262	5,669	18,419
Anuradhapura	0.3801	0.4003	5,440	18,231
Badulla	0.3807	0.4284	4,898	17,422
Batticaloa	0.3212	0.4077	5,461	16,488
Colombo	0.4891	0.4654	9,719	36,015
Galle	0.4403	0.4243	5,386	19,851
Gampaha	0.4414	0.4248	7,443	26,731
Hambantota	0.3373	0.4087	5,628	18,087
Jaffna	0.3672	0.4168	4,756	16,921
Kalutara	0.3356	0.4095	6,389	20,305
Kandy	0.4732	0.4527	5,656	20,643
Kegalle	0.3080	0.3921	4,765	15,021
Kilinochchi	0.4853	0.4716	5,932	21,660
Kurunegala	0.8070	0.4873	5,609	28,601
Mannar	0.1784	0.3206	4,889	11,974
Matale	0.3462	0.4215	5,242	17,141
Matara	0.3195	0.4060	5,583	17,229
Monaragala	0.4657	0.4456	4,757	19,152
Mullaitivu	0.3091	0.4145	4,824	13,861
Nuwara Eliya	0.6049	0.4153	3,911	18,537
Polonnaruwa	0.5477	0.4245	5,719	22,674
Puttalam	0.4577	0.4320	5,385	20,411
Ratnapura	0.5605	0.4614	4,784	21,264
Trincomalee	0.3660	0.4079	5,786	18,175
Vavuniya	0.3629	0.4365	9,350	27,098

Figure 4.2: Variation of mean inequality measured by Theil index across districts

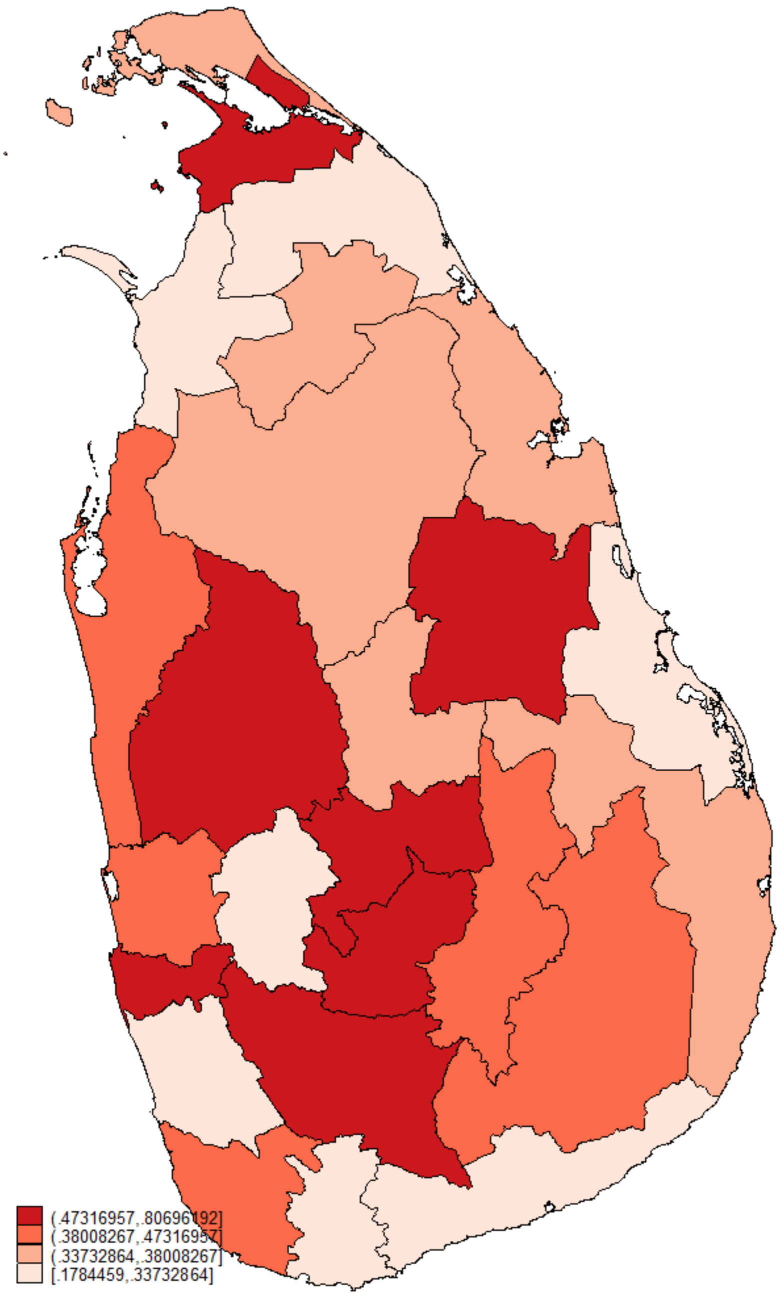


Figure 4.3: Variation of mean inequality measured by Theil index across districts, graphical representation

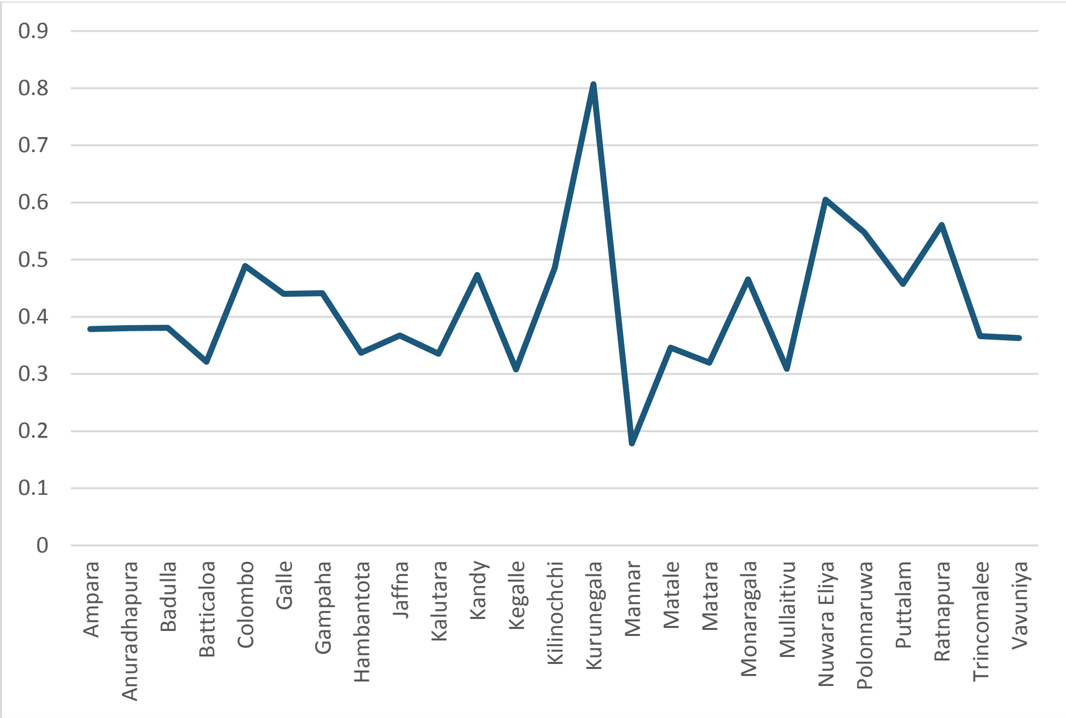


Figure 4.4 presents within district variation of inequality as measured by Theil index over time. No such variation is presented for Jaffna, Kilinochchi and Mannar Districts as these districts were covered only in the last survey wave, i.e., 2012/13. We can observe a considerable variation of inequality over time for almost all the districts and this is the variation we exploit in this paper.

Figure 4.4: Variation of inequality measured by Theil index by districts over time

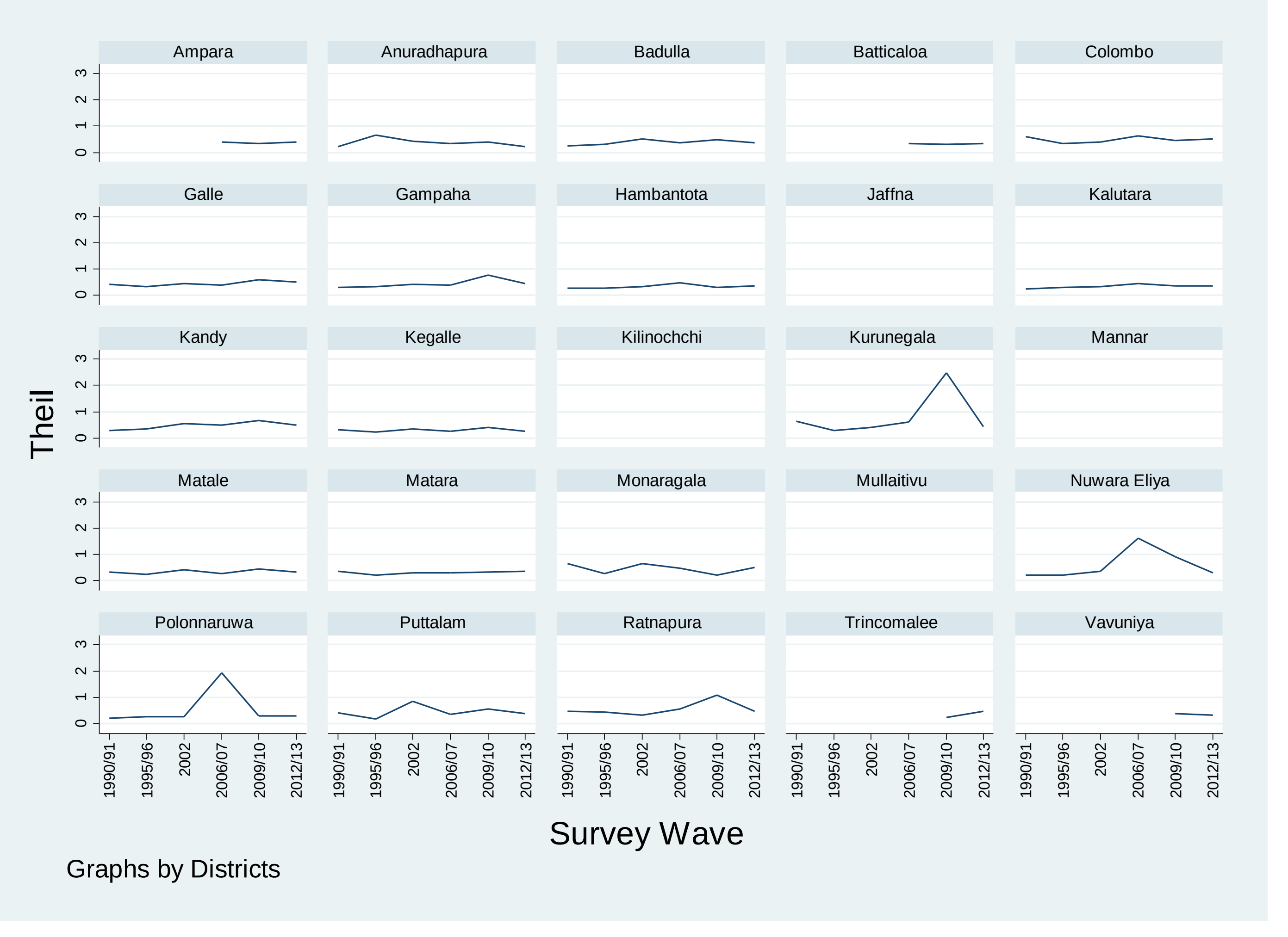
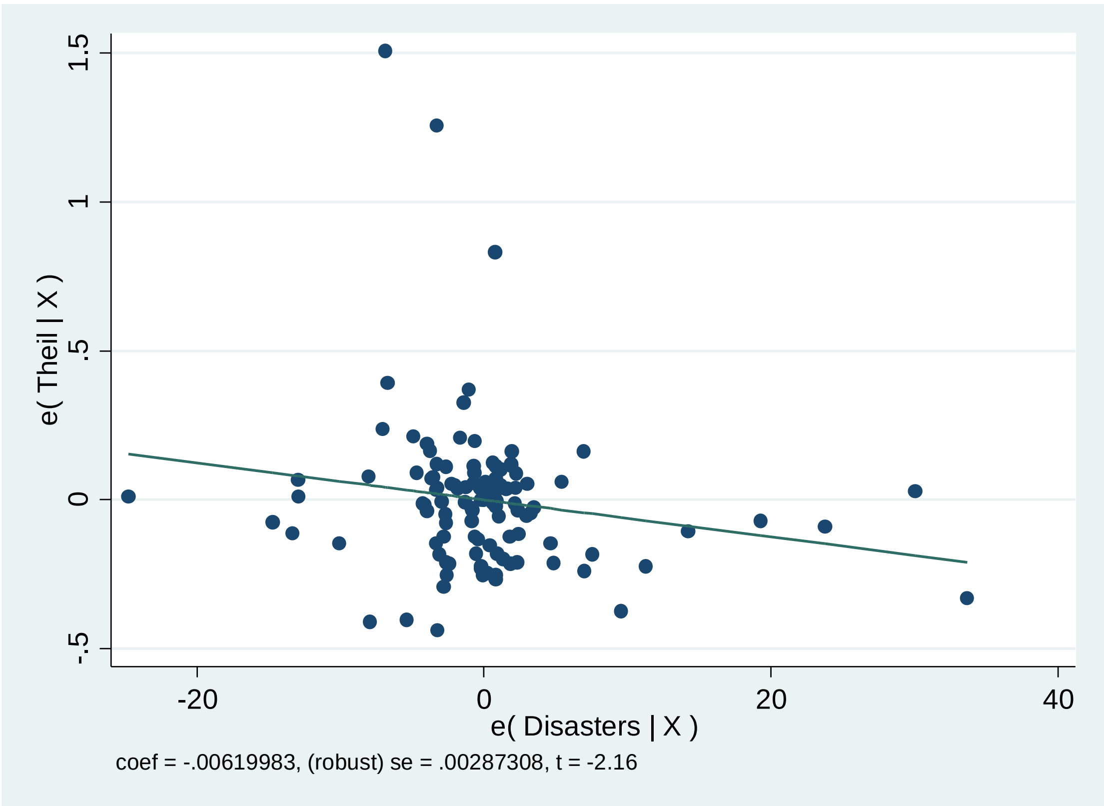


Figure 4.5 depicts the relationship between current natural disaster affected population (%) and income inequality measured by Theil index after controlling for disaster lags, time invariant district fixed effects and time fixed effects. There appears to be a significant negative correlation between disasters and income inequality suggesting a possible reduction of income inequality by natural disasters.

Figure 4.5: Association between Theil index and natural disasters



Notes: Above graphical representation is obtained using avplot command in Stata/IC 14.1 after controlling for disaster lags, district and time fixed effects.

4.2.2 Empirical Model

We employ a panel regression estimator with district and time fixed effects as the main estimation strategy in our analysis. Fixed effects estimator is chosen since district and time fixed effects control for time-invariant spatial heterogeneity among districts and time-variant shocks that simultaneously affect all the districts, respectively. As such, this approach reduces any potential endogeneity issue.

The panel regression equation of the baseline model is as follows;

$$Inequality_{it} = \alpha_i + \beta_t + \gamma\ Dis_{it} + \Gamma Dis_{i,t-n} + \varepsilon_{it} \tag{4.1}$$

where income inequality as measured by Theil index in district *i* in Sri Lanka for survey time *t*, is the dependent variable. *Dis* is our variable of interest, disaster impact measured as the percentage of population affected due to all natural disasters occurred during the survey year in each district. We also include lagged disasters in the regression. Given the data availability, for each survey time five disaster lags are included in the regression in addition to the current disaster variable. Terms α_i and β_t are the district and time fixed effects included in the model, respectively. The final term ε_{it} in the equation is the error term. Errors are clustered at district level.

We check against omitted variable bias by adding more control variables, such as median household income, headcount index, % of poor households and other indicators which reflect social and economic status of households. In addition to the Theil index, we employ other alternative inequality measures such as the Gini coefficient, inter quartile range and inter quintile range of average income as the dependent variable. We rerun regressions excluding the extreme survey waves, i.e., 2006/07 which was after 2004 tsunami and 2009/10 survey which was after the ending of war/terrorism, to ensure that results are not driven by these extreme waves.

Apart from the panel fixed effect estimator we use alternative estimators such as ordinary least squares (OLS) and System GMM to support our findings; see Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998), (Roodman, 2009a) and (Roodman, 2009b). Once we are convinced that natural disasters affect income inequality, we explore how natural disasters affect level of income itself, particularly in different quintiles. As it is evident that income of all quintiles is reduced in the presence of disasters, we decompose inequality measured by Theil index into income components. We compare results with the differences in income composition of poor and rich quintiles as this exercise explains findings.

As we are using the household income and expenditure survey data, we investigate whether there is any relationship between household expenditure inequality and natural disasters. We expand our analysis to disaster subgroups and repeat our analyses excluding biological disasters as the mechanisms are so different. Finally, we repeat our analysis without meteorological disasters since they appear to increase income inequality as the relative loss due to such disasters decreases with income.

4.3 Results

4.3.1 Base Model

Table 4.3: Results for regressing income inequality on natural disasters: Base model

	Dependent variable: Income inequality (Theil)
	Fixed Effects
Disaster (% Population Affected)	-0.00620**
	(0.00252)
Disaster_lag1	0.000640
	(0.00106)
Disaster_lag2	-0.00338*
	(0.00166)
Disaster_lag3	-0.00414*
	(0.00208)
Disaster_lag4	0.00473**
	(0.00225)
Disaster_lag5	0.000189
	(0.00144)
Observations	117
Number of Districts	25
R-squared	0.186

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Model includes a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Results of the baseline model are given in Table 4.3. We find statistically significant negative impact of natural disasters that occurred in the same year, two years and three years prior to the survey on income inequality measured by Theil index. However, there appear to be a significant positive impact of natural disasters that took place 4 years before the survey on income inequality. Accordingly, an increase of current disaster affected population by one percentage point would reduce income inequality measured by Theil index by 0.0062 points, *ceteris paribus*.

As this interpretation may suffer from lack of immediate apprehension, we provide here a hypothetical illustration for clarity. Using the latest 2012/13 Survey data, national inequality measured by Theil index is 0.46008. If we deduct the income of each household in the 5th quintile by 0.483% and redistribute the proceeds equally among all households in the poorest quintile, the resultant Theil is 0.45388 (i.e. 0.46008 - 0.0062). Thus, an increase in disasters to affect one extra percentage point of people is equivalent to a half percent income tax on the richest fifth for redistribution to the poorest fifth.

In our regressions we cluster errors at district level. Since administrative policy implementation is mostly carried out at provincial level, we alternatively clustered at provincial level also considering the potential spatial correlation of natural disasters and found similar results.

4.3.2 Disaster Impact on Inequality of Components of Income

To disentangle the ways by which income inequality is decreased due to natural disasters, we decompose income into its components, and compute the Theil index for each component.

Table 4.4 and Table 4.5 reveal that the negative impact of natural disasters on income inequality is not driven by receipts (which include any disaster relief payments) or by any foreign or domestic remittances households receive after disasters. Natural disasters and their immediate lags significantly decrease non-agricultural income inequality and non-seasonal agricultural income inequality, but increase seasonal agricultural income inequality. Given the strict labour laws which ensure the rights of employees in formal employment, Sri Lanka does not see any effect of natural disasters on employment income inequality.

Table 4.6 and Table 4.7 show the composition of household income varies across quintiles. Rich quintiles receive a higher share of their income from non-agricultural sources such as business activities and non-seasonal agricultural activities compared to the poor whilst the share of income the poor receive from these sources is much lower.

Further, poorest households earn a higher share of income from seasonal agriculture most probably weather dependent, compared to the richest quintile.

Table 4.4: Results for regressing income inequality on natural disasters, by income component

	Dependent variable: Inequality – Component of income (Theil)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total	Employ	Agri	Agri_Other	Non_Agri	Kind	Receipts	Remittances
Disaster	-0.00620**	0.000707	0.00200*	-0.00961**	-0.0112**	-0.00272	9.03e-05	0.00313
	(0.00252)	(0.000639)	(0.00117)	(0.00396)	(0.00525)	(0.00160)	(0.00155)	(0.00212)
Dis_lag1	0.000640	0.000133	-0.00100	0.00326	-0.000655	-0.000824	0.000355	0.000733
	(0.00106)	(0.000256)	(0.000695)	(0.00249)	(0.00146)	(0.000648)	(0.000630)	(0.000832)
Dis_lag2	-0.00338*	-0.000314	0.00209**	-0.00181	-0.00592**	0.000620	-0.00134	0.00183*
	(0.00166)	(0.000495)	(0.000884)	(0.00238)	(0.00248)	(0.000758)	(0.000907)	(0.000997)
Dis_lag3	-0.00414*	-0.000763	-0.00260	-0.0127***	-0.00525	-6.12e-05	0.000392	-0.000528
	(0.00208)	(0.000636)	(0.00287)	(0.00431)	(0.00569)	(0.00190)	(0.00150)	(0.00230)
Dis_lag4	0.00473**	-0.000156	0.00221	0.00513	0.0128**	-0.000331	0.00398**	-0.00101
	(0.00225)	(0.000623)	(0.00156)	(0.00515)	(0.00530)	(0.00148)	(0.00147)	(0.00164)
Dis_lag5	0.000189	0.000207	-0.000370	0.00153	0.000430	-0.00102	0.000755*	0.000590
	(0.00144)	(0.000244)	(0.000491)	(0.00200)	(0.00352)	(0.000682)	(0.000419)	(0.000611)
Observations	117	117	117	117	117	117	117	117
R-squared	0.186	0.114	0.244	0.251	0.112	0.510	0.515	0.156
Districts	25	25	25	25	25	25	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4.5: Summary: How do disasters affect inequality of components of income?

	Dependent variable: Inequality – Component of income (Theil)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total Income	Employ	Agri	Agri_Other	Non_Agri	Kind	Receipts
Disasters	↓		↑	↓	↓		
Dis_lag1							
Dis_lag2	↓		↑		↓		
Dis_lag3	↓			↓			
Dis_lag4	↑				↑		↑
Dis_lag5							↑

Table 4.6: Average share of income by components (%)

	Employ	Agri	Agri_other	Non_agri	Kind	Receipts
Q1	44.22	7.01	4.98	1.43	22.63	19.80
Q2	47.18	5.40	6.69	9.72	15.86	15.07
Q3	48.06	5.13	7.36	9.58	14.60	15.27
Q4	44.21	4.82	7.69	12.73	14.10	16.44
Q5	31.29	3.32	11.83	24.48	11.53	17.43
Disaster Impact		↑	↓	↓		

Table 4.7: Share of income by component (%)

		Employ	Agri	Agri_other	Non_agri	Kind	Receipts	Total
1990/91	Q1	43.28	7.94	6.34	6.55	15.76	20.21	
	Q2	48.58	6.49	7.99	9.08	12.30	15.47	
	Q3	50.26	6.44	8.79	8.07	11.74	14.70	
	Q4	46.39	6.34	9.09	12.56	12.00	13.56	
	Q5	34.74	4.67	10.21	25.36	11.98	12.86	
1995/96	Q1	46.38	7.42	5.97	1.12	20.78	18.39	
	Q2	49.59	6.08	7.63	9.21	15.24	12.37	
	Q3	51.42	4.70	7.46	9.93	14.40	12.01	
	Q4	48.77	3.90	7.11	12.14	14.76	12.99	
	Q5	41.95	2.18	7.95	21.51	14.32	12.29	
2002	Q1	71.20	8.71	6.37	-45.57	38.31	21.00	
	Q2	52.61	4.19	6.21	9.81	17.35	9.76	
	Q3	50.84	3.68	6.66	10.87	16.72	11.30	
	Q4	47.58	2.98	6.24	12.84	16.77	13.46	
	Q5	35.23	1.82	8.34	22.20	14.13	18.17	
2006/07	Q1	45.49	4.59	3.78	-3.32	32.75	16.76	
	Q2	45.55	3.03	4.43	10.42	22.88	13.62	
	Q3	43.78	2.59	5.17	12.41	19.79	16.19	
	Q4	40.23	1.95	6.17	13.99	17.90	19.75	
	Q5	28.39	1.36	13.08	20.11	10.40	26.45	
2009/10	Q1	46.15	6.13	1.99	-10.47	36.81	19.37	
	Q2	43.21	4.26	4.17	10.74	22.64	14.88	
	Q3	42.50	3.77	5.06	12.31	20.00	16.48	
	Q4	39.75	3.09	5.36	12.53	17.91	21.52	
	Q5	22.45	1.75	16.47	28.69	10.08	20.58	
2012/13	Q1	42.37	4.10	0.89	-4.84	37.95	19.58	
	Q2	43.96	3.12	4.40	11.23	21.70	15.57	
	Q3	44.56	2.47	4.54	11.97	19.12	17.35	
	Q4	39.90	2.09	5.12	12.97	16.89	23.06	
	Q5	26.62	1.26	13.88	20.34	11.03	26.81	
Significant Impact	Dis		↑	↓	↓			↓
	Dis_lag1							
	Dis_lag2		↑		↓			↓
	Dis_lag3			↓				↓
	Dis_lag4				↑		↑	↑
	Dis_lag5						↑	

4.4 Robustness Checks

4.4.1 Balanced Panel

The number of districts covered in the survey changes over time as some districts of Northern and Eastern provinces were not covered in earlier waves due to the ongoing civil war at that time. To ensure that results are not driven by the newly added districts, we rerun our baseline regression with a balanced panel of 17 districts for the six waves. Results as presented in Table 4.8 support our original findings although the significance level of coefficients on the variables of interest is lower compared to the base model.

Table 4.8: Results for regressing income inequality on natural disasters: Base model with a balanced panel of 17 districts

	Dependent variable: Income inequality (Theil)
	Fixed Effects
Disaster (% Population Affected)	-0.00651*
	(0.00345)
Disaster_lag1	0.000532
	(0.000992)
Disaster_lag2	-0.00218
	(0.00177)
Disaster_lag3	-0.00687*
	(0.00348)
Disaster_lag4	0.00122
	(0.00306)
Disaster_lag5	-0.000260
	(0.00183)
Observations	102
Number of Districts	17
R-squared	0.204

Notes: Balanced panel of 17 districts with district level inequality measures for six waves of surveys, corresponding contemporaneous and lagged disaster data. Model includes a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.4.2 Additional Controls

The above results hold in the presence of other control variables, namely, real median household income (in constant 2006 Rs.), poverty head count index (HCI) and the share of poor households (Table 4.9). The HCI is the percentage of population below the official poverty line, which is based upon the real total expenditure per person per month; a household with members whose per capita expenditure is below the official poverty line is considered as a poor household (Department of Census and Statistics, 2015).

Table 4.9: Results for regressing income inequality on natural disasters: Controls

	Dependent variable: Income inequality (Theil)	
	(1)	(2)
Disaster (% Population Affected)	-0.00805***	-0.00947***
	(0.00224)	(0.00300)
Disaster_lag1	-0.000313	-0.000435
	(0.00134)	(0.00165)
Disaster_lag2	-0.00308**	-0.00404
	(0.00134)	(0.00249)
Disaster_lag3	-0.00585**	-0.00831*
	(0.00268)	(0.00450)
Disaster_lag4	0.00650**	0.00504
	(0.00260)	(0.00311)
Disaster_lag5	0.000152	9.85e-06
	(0.00132)	(0.00113)
Real Median Household Income (logged)	0.0986	-0.0799
	(0.237)	(0.281)
HCI	0.0190*	
	(0.00950)	
% of Poor Households		0.0174
		(0.0113)
Observations	117	100
R-squared	0.245	0.203
Number of Districts	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.4.3 Alternative Inequality Metrics

We check whether our results hold for different inequality measures such as Gini coefficient, inter quintile range for average income and inter quartile range. As shown in Table 4.10, disasters and their immediate lags reduce income inequality not only measured by the Theil index but also by the Gini coefficient and the inter quintile range of average income. Further, disasters occurred in the previous year seem to significantly reduce inter quartile range of income.

Table 4.10: Results for regressing income inequality on natural disasters: Alternative inequality metrics, Gini coefficient, inter quintile range (IQ^5R), and inter quartile range (IQ^4R)

	Dependent variable: Income inequality		
	(1)	(2)	(3)
	Gini	IQ^5R (ln)	IQ^4R (ln)
Disaster (% Pop. Affected)	-0.00139***	-0.00453***	0.000759
	(0.000396)	(0.00126)	(0.000718)
Disaster_lag1	-3.73e-05	-0.000605	-0.000764**
	(0.000242)	(0.000991)	(0.000279)
Disaster_lag2	-0.000596**	-0.00235**	-0.000268
	(0.000227)	(0.000948)	(0.000593)
Disaster_lag3	-0.00128**	-0.00557**	-0.000123
	(0.000531)	(0.00210)	(0.000646)
Disaster_lag4	0.00156**	0.00627**	0.000621
	(0.000646)	(0.00275)	(0.00184)
Disaster_lag5	2.73e-05	-0.000245	4.59e-05
	(0.000214)	(0.000830)	(0.000378)
Real Median Household Income (logged)	-0.0584	0.570*	0.629**
	(0.0490)	(0.285)	(0.230)
HCI	0.00252	0.00512	-0.00391
	(0.00152)	(0.00850)	(0.00312)
Observations	117	117	117
R-squared	0.411	0.808	0.945
Number of Districts	25	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

When we run the regression for alternative inequality measures with current disasters and additional relevant controls on access to safe drinking water and hygienic facilities, structure of the house and possession of movable properties which reflect socio-economic status of households, we observe that current disasters significantly decrease income inequality measured by alternative inequality metrics (Table 4.11).

Table 4.11: Results for regressing income inequality on natural disasters: Current disasters with additional controls

	Dependent variable: Income inequality		
	(1) Theil	(2) Gini	(3) IQ5R (ln)
Disaster (% Pop. Affected)	-0.0151***	-0.00209***	-0.00912***
	(0.00492)	(0.000736)	(0.00243)
% of HH without safe drinking water	0.0140*	0.00219*	0.00483
	(0.00757)	(0.00122)	(0.00502)
% of HH without a toilet	-0.0161	-0.00364	-0.0207
	(0.0310)	(0.00529)	(0.0199)
% of HH with no rooms	-0.0532	-0.00588	0.0117
	(0.0513)	(0.00909)	(0.0345)
% of HH without electric equipment	0.0210	0.00124	-0.000979
	(0.0128)	(0.00203)	(0.00825)
% of HH without vehicles	-0.00183	0.00136	-0.00370
	(0.0120)	(0.00198)	(0.00772)
Observations	61	61	61
R-squared	0.232	0.202	0.177
Number of Districts	25	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous disaster data. IQ5R is the inter quintile range for average income. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.4.4 Outliers

We exclude the survey wave 2006/07 which was after the Indian Ocean tsunami in December 2004 and the survey wave 2009/10 which was after the ending of 30 years long terrorist war alternatively and simultaneously, results still remain significant (Table 4.12).

Table 4.12: Results for regressing income inequality on natural disasters: Excluding possible outlier waves

	Dependent variable: Income inequality (Theil)		
	(1)	(2)	(3)
	Without wave just after Tsunami	Without wave after ending of war	Without both the waves
Disaster (% Pop. Affected)	-0.00541**	-0.00399*	-0.00116*
	(0.00260)	(0.00230)	(0.000617)
Disaster_lag1	0.000326	0.00104	0.000493
	(0.00105)	(0.00115)	(0.000786)
Disaster_lag2	-0.00174*	-0.00260	0.000246
	(0.000921)	(0.00174)	(0.00144)
Disaster_lag3	-0.00229	-0.00416**	-0.00750**
	(0.00350)	(0.00169)	(0.00298)
Disaster_lag4	0.00504**	0.00298	-2.12e-05
	(0.00200)	(0.00184)	(0.00325)
Disaster_lag5	0.00226	-0.000598	-0.000578
	(0.00406)	(0.00107)	(0.00116)
Observations	98	95	76
R-squared	0.228	0.212	0.367
Number of Districts	25	25	25

Notes: Panel of district level inequality measures for five waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.4.5 Alternative Estimators

As a further robustness check, we re-estimate the model using ordinary least squares (OLS) and, difference and system generalised method of moments (GMM) estimators. As apparent from Table 4.13, alternative estimators, OLS and system GMM yield consistent results. Difference GMM also yields consistent results at least with respect to the sign on the coefficient. In this exercise, we restrict our explanatory variables to current disasters and HCI. The GMM uses lagged values of independent variables which are not strictly exogenous as internal instruments. Therefore, the inclusion of additional disaster lags in the model may complicate the process.

Table 4.13: Results for regressing income inequality on natural disasters: Alternative estimators

	Dependent variable: Income inequality (Theil)			
	(1)	(2)	(3)	(4)
	FE	OLS	Diff. GMM	Sys. GMM
Disaster (% Pop. Affected)	-0.00621**	-0.00362**	-0.00509	-0.00821**
	(0.00275)	(0.00152)	(0.00363)	(0.00363)
HCI	0.0147	0.00284	0.0166	0.0182
	(0.00910)	(0.00361)	(0.0128)	(0.0146)
Observations	117	117	92	117
R-squared	0.198	0.115		
Number of Districts	25		22	25
Number of Instruments			10	11
Arellano-Bond Test AR(1)			0.067	0.088
Arellano-Bond Test AR(2)			0.714	0.652
Hansen Test			0.234	0.213

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Lags used to instrument the endogenous variables in Difference GMM and system GMM regressions limited to 10.

4.4.6 Disaster Impact on Income

As shown in Table 4.14, current natural disasters negatively affect mean household income whilst the disasters occurred in the previous year negatively affect median household income. Income of the poorest quintile is reduced by current disasters and disasters occurred three years before. Income of the middle quintiles is reduced by the disasters occurred in the previous year. Richest quintile's income is decreased by current disasters and disasters occurred two and three years before. So, we find clear evidence that income of all the quintiles is affected by natural disasters.

Table 4.14: Results for regressing income on natural disasters

	Dependent variable: Household income (logged)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mean	Median	Q1	Q2	Q3	Q4	Q5
Disasters	-0.00507**	-0.00180	-0.0109***	-0.00212	-0.00172	-0.00152	-0.00613***
	(0.00185)	(0.00154)	(0.00387)	(0.00159)	(0.00163)	(0.00166)	(0.00186)
Dis_lag1	-0.000724	-0.00101***	0.00151	-0.00102***	-0.00108***	-0.00127***	-0.000596
	(0.000537)	(0.000299)	(0.00205)	(0.000331)	(0.000292)	(0.000301)	(0.000832)
Dis_lag2	-0.00104	0.000328	0.00104	0.000502	0.000298	0.000107	-0.00209**
	(0.000691)	(0.000561)	(0.00127)	(0.000763)	(0.000567)	(0.000475)	(0.000945)
Dis_lag3	-0.00358*	-0.00124	-0.00598*	-0.00111	-0.000954	-0.000852	-0.00546**
	(0.00192)	(0.00141)	(0.00304)	(0.00174)	(0.00142)	(0.00134)	(0.00239)
Dis_lag4	0.00209	0.000165	0.00269	-5.09e-05	0.000146	0.000795	0.00485*
	(0.00157)	(0.00117)	(0.00263)	(0.00112)	(0.00113)	(0.00133)	(0.00235)
Dis_lag5	0.000563	0.000395	0.00180	0.000293	0.000355	0.000348	0.000333
	(0.000797)	(0.000424)	(0.00114)	(0.000473)	(0.000437)	(0.000508)	(0.000967)
Observations	117	117	113	117	117	117	117
R-squared	0.852	0.905	0.414	0.882	0.907	0.922	0.799
Districts	25	25	24	25	25	25	25

Notes: Panel of district level measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.4.7 Disasters and Household Expenditure Inequality

We repeat our analysis for household expenditure inequality. As in the previous analysis, we calculate per adult equivalent household expenditure and then calculate district wise inequality measures for each survey wave. When we estimate our baseline specification using panel fixed effects estimator, we do not find any impact of natural disasters on expenditure inequality measured either by Theil index or Gini coefficient (Table 4.15). There may be two plausible explanations for this. One is that households suffer income losses due to natural disasters disproportionately across quintiles, however, they act as if they have a permanent income when it comes to expenditure and therefore do not change their spending behaviour. The other is that all the households reduce their expenditure proportionately across quintiles in the presence of natural disasters. Both scenarios would lead to no change in expenditure inequality among households due to natural disasters.

Table 4.15: Results for regressing expenditure inequality on natural disasters

	Dependent variable: Expenditure inequality	
	(1)	(2)
	Theil	Gini
Disaster (% Population Affected)	0.00116	0.000239
	(0.00145)	(0.000318)
Disaster_lag1	0.000136	4.41e-05
	(0.000130)	(8.06e-05)
Disaster_lag2	0.000427	0.000205
	(0.000321)	(0.000146)
Disaster_lag3	-5.63e-05	-5.06e-05
	(0.000434)	(0.000255)
Disaster_lag4	-0.00124	-0.000379
	(0.00131)	(0.000578)
Disaster_lag5	6.81e-05	6.54e-05
	(0.000172)	(6.67e-05)
Observations	117	117
R-squared	0.321	0.514
Number of Districts	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.4.8 Disaster Subgroups and Income Inequality

Accepting the fact that natural disasters differ in nature, intensity, duration and impact, we repeat our analysis by disaster subgroups. Table 4.16 shows a significant negative impact of geophysical, hydrological and meteorological disasters on different income inequality measures.

Table 4.16: Results for regressing income inequality on natural disasters by disaster type

	Dependent variable: Income inequality			
	(1)	(2)	(3)	(4)
	Theil	Gini	IQ^4R (ln)	IQ^5R (ln)
Biological	0.0645	0.00520	0.0447*	0.0157
	(0.146)	(0.0198)	(0.0238)	(0.0782)
Climatic	-0.00411	-0.000545	0.000362	-0.00149
	(0.00328)	(0.000485)	(0.00144)	(0.00128)
Geophysical	-0.181*	-0.0587***	-0.0250	-0.185***
	(0.0879)	(0.0144)	(0.0201)	(0.0558)
Hydrological	-0.00729	-0.00123	-0.00261	-0.00875**
	(0.00574)	(0.00135)	(0.00246)	(0.00398)
Meteorological	-0.00102	-5.91e-05	-0.00760***	-0.0115***
	(0.00443)	(0.00100)	(0.00153)	(0.00227)
Observations	117	117	117	117
R-squared	0.164	0.333	0.902	0.786
No. of Districts	25	25	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous disaster data. IQ^4R is the inter quartile range. IQ^5R is the inter quintile range for average income. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Some argue that biological disasters are very different from other natural disasters. We therefore replicate the analysis excluding biological disasters from total disasters. This exercise derives similar results as for the base model (see Table 4.17).

As shown in Table 4.18, different natural disaster subgroups affect mean, median household incomes and income across quintiles differently. Meteorological disasters may appear to increase income inequality on the face of results, as the relative loss due to such disasters decreases with income. Nevertheless, we do not find evidence to that effect; see Table 4.16. As a further step, we rerun our regression excluding meteorological disasters from total disasters to ensure that it is not linked with the metrics being used (Table 4.19).

Results are very similar to the base model's results.

Table 4.17: Results for regressing income inequality on natural disasters excluding biological disasters

	Dependent variable: Income inequality (Theil)
	Fixed Effects
Disaster (% Population Affected)	-0.00624**
	(0.00256)
Disaster_lag1	0.000627
	(0.00106)
Disaster_lag2	-0.00341*
	(0.00167)
Disaster_lag3	-0.00421*
	(0.00209)
Disaster_lag4	0.00465*
	(0.00226)
Disaster_lag5	0.000184
	(0.00144)
Observations	117
Number of Districts	25
R-squared	0.186

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4.18: Results for regressing income on different disaster subgroups

	Dependent variable: Household Income (logged)						
	(1)	(2)	(3)	(4)	(5)	(5)	(7)
	Mean	Median	Q1	Q2	Q3	Q4	Q5
Biological	0.0443	0.0398***	-0.0268	0.0300***	0.0360***	0.0276*	0.0283
	(0.0599)	(0.0117)	(0.0374)	(0.00981)	(0.0111)	(0.0140)	(0.0805)
Climatic	-0.00368*	-0.00117	-0.0111**	-0.00141	-0.00101	-0.000659	-0.00347
	(0.00213)	(0.00124)	(0.00478)	(0.00111)	(0.00128)	(0.00131)	(0.00207)
Geophysical	-0.110***	0.0361*	-0.430***	0.0227	0.0339*	0.0152	-0.202***
	(0.0318)	(0.0188)	(0.0601)	(0.0182)	(0.0187)	(0.0178)	(0.0516)
Hydrological	-0.0059***	-0.00287	-0.00595	-0.00350	-0.00317	-0.00320	-0.00826**
	(0.00184)	(0.00232)	(0.00424)	(0.00236)	(0.00240)	(0.00234)	(0.00371)
Meteorological	-0.0118***	-0.0096***	-0.0137***	-0.0118***	-0.0098***	-0.0095***	-0.0124***
	(0.00151)	(0.00176)	(0.00331)	(0.00185)	(0.00181)	(0.00165)	(0.00259)
Observations	117	117	113	117	117	117	117
R-squared	0.847	0.903	0.413	0.883	0.905	0.918	0.788
Districts	25	25	24	25	25	25	25

Notes: Panel of district level measures for six waves of surveys with corresponding contemporaneous disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4.19: Results for regressing income inequality on natural disasters excluding meteorological disasters

	Dependent variable: Income inequality (Theil)
	Fixed Effects
Disaster (% Population Affected)	-0.00646**
	(0.00248)
Disaster_lag1	0.000460
	(0.00101)
Disaster_lag2	-0.00281*
	(0.00156)
Disaster_lag3	-0.00524**
	(0.00219)
Disaster_lag4	0.00463**
	(0.00219)
Disaster_lag5	9.24e-05
	(0.00136)
Observations	117
Number of Districts	25
R-squared	0.187

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.5 Discussion and Conclusion

We explore the impact of natural disasters on income inequality in Sri Lanka at district level, the first study of this nature for the country. We construct a unique panel dataset for the purpose that includes *inter alia* district wise inequality/income measures and percentages of population affected due to natural disasters in each district for the six survey periods of the HIES series between 1990 and 2013. Using panel fixed effects estimator as the main empirical strategy we find that contemporaneous natural disasters and their immediate lags decrease district level income inequality as measured by the Theil index, and substantially so. These results are robust across alternative inequality metrics, sub-samples and alternative estimators. However, we do not find any evidence to the effect that natural disasters affect household expenditure inequality. This is possible if households do not change their expenditure patterns despite their income being affected by disasters or if they might reduce their expenditure proportionately across income quintiles as a result of disaster consequences.

Further analysis suggests that although natural disasters negatively affect household income across all the quintiles, rich quintiles disproportionately bear direct disaster damages at a higher cost. Even though the poor are more vulnerable to disasters, when the poor live a subsistence lifestyle and if they do not possess or own much material assets, their losses will be less compared to the rich. Rich may lose income deriving capital assets more due to destruction and through sale as a coping strategy. On the other hand, if the poor are mainly engaged in low-skilled or unskilled labour they can easily diversify their income sources in the aftermath of a natural disaster. Whilst the rich may suffer profit losses, disasters may open the poor a door for new opportunities. It is evident from our decomposition results that natural disasters decrease non-agricultural income inequality and non-seasonal agricultural income inequality. Household income composition shows that the richest quintile receives a much higher share of their income from these very activities compared to the poor. When the rich suffer greater losses in profits and income due to disasters, it is inevitable that household income inequality would decrease, however, at the expense of the rich. Our findings warrant policies to safeguard the interests of middle and higher income groups in disaster consequences.

To achieve effective poverty reduction and inclusive growth, the desired is a lower inequality in general. McKay and Pal (2004) present strong evidence that lower initial inequality has a favourable influence on subsequent consumption across many Indian states. Although, lower income inequality is desirable for poverty reduction and to achieve inclusive growth, as a low income inequality derived through higher damages caused to middle and richer quintiles does not reflect true distributive justice, change of inequality in the face of natural disasters should be read with caution. Further, policy makers should give sufficient consideration to natural disasters in designing and implementing policies to promote poverty reduction and inclusive economic growth.

Our study does not capture potential internal migration as a result of natural disasters which would otherwise have explained the decrease in income inequality. This would be a limitation to our analysis. Future research can address this issue although this study is constrained with data availability. Further, Sri Lanka is just one country out of many that face various natural disaster consequences and issues relating to distributive justice at the same time. Furthermore, as Sri Lanka is a lower middle income country with an economy oriented towards services and industry, it could not represent lower income countries which mainly depend on agriculture and are more vulnerable to disasters. Therefore, this analysis could be repeated for other countries with better data as an avenue for future research.

5 Conclusion

This thesis examined the impact of natural disasters on three important economic aspects which contribute to the achievement of economic development and distributive justice. Although destructive natural catastrophes are considered as a hindrance for development, indirect effect of disasters on development through their impact on financial development and foreign aid diversification cannot be undermined. If the contraction of income inequality we sometimes observe in developing economies comes at the expense of middle and high income earners, it does not reflect true distributive justice and thus should be a grave concern for policy makers. In this concluding chapter, I summarise the findings, policy implications and limitations of my thesis and the potential future research avenues it opens up.

The first empirical paper explored the impact of natural disasters on financial development proxied by private credit. It found that companies and households get deeper into debt after a natural disaster in the short run. It presented evidence for credit deepening in the long run, too. These findings invite relevant policy makers in disaster vulnerable countries to take well informed and well thought decisions with respect to financial inclusion, domestic bank lending and directed credit. Hallegatte et al. (2017, p. 2) identify opportunities for action and policy priorities at the country level, to make people more resilient to disasters. They highlight expanding financial inclusion as one of the policies to reduce well-being losses. As immediate and unconstrained credit is essential for a speedy recovery in poorer countries, policies should be implemented to enhance credit availability, especially to reach individuals with lower credit worthiness due to non-availability of acceptable securities. Specifically, policies are warranted to enhance financial literacy of rural people so that they would be in a position to accumulate their wealth in the forms (e.g. financial assets such as deposits and financial instruments) which are not subject to easy destruction in the face of natural disasters. Furthered financial literacy helps people to be part of the formal financial system which in turn increases their access to credit when need arises. Also, financial sector regulators (Central Bank or the Monetary Authority, as the case may be) in disaster prone developing countries can impose directed credit directives to their lending institutions which make it obligatory for such institutions to dedicate a certain share of their lending portfolio towards specific sectors.

On the limitation side of my study, I use private credit to proxy financial development. It is to be noted that private credit represents only one aspect, i.e., depth of financial development which is multi-faceted. This poses the question whether the mere deepening in credit could be interpreted as financial development. Further, financial markets are less well developed in poorer countries which are more vulnerable to disasters and the role played by formal credit therein in disaster consequences might be small. Therefore, my study may not be capturing the true image of the least developed world. Thus, further research can be done with much appropriate proxies for financial development as and when data become available in the future.

This paper used EM-DAT data to construct the disaster measure used in the analysis. Even though I consider EM-DAT database as the best available disaster data set and most of the disaster literature is based on this data, it should be noted that some scholars question the validity of these data. One reason for this is the arbitrary thresholds (i.e. reported death toll of 10 or more; 100 people reported affected; a call for international assistance; or the declaration of the state of emergency) they use for a disaster to be entered into their database (Miao & Popp, 2014). Their sources of data maybe lacking the necessary expertise to estimate economic losses and their data maybe suffering from measurement error. In some instances, even a severe disaster may not kill as per the database (Cavallo & Noy, 2011; Gassebner et al., 2010; Klomp, 2014). I also noticed with surprise instances where there are deaths but none has been affected, which is highly unlikely. Indeed, I repeat my analysis with alternative disaster data, i.e., the ifo GAME data, which are purely based on disaster intensities and yield consistent results supporting my findings. However, then the question arises whether we can consider natural catastrophes as natural disasters by definition, knowing nothing about how they affected man or his artifacts (Dacy & Kunreuther, 1969). I do not see any immediate remedy for this as we cannot have it both ways.

In this paper I used nationally aggregate data. Changes at the aggregate level are open to misinterpretation and may obscure the actual mechanisms. Therefore, the analysis here should be repeated with micro data. I found that natural disasters affect financial development. Earlier papers found that financial development affects vulnerability to natural disasters. The analysis should therefore be repeated with a dynamic model of simultaneous equations. These issues are deferred to future research.

The second empirical paper raised the question whether natural disasters affect foreign aid concentration in recipient countries. I found that natural disasters lead to a reduction in aid concentration. Natural disasters appear to attract not only disaster related aid but also aid aimed at other development aspects. Therefore, relevant policy makers should make sure that these donations are invested effectively on the desired purposes. However, as per the existing literature it appears that aid concentration negatively affects the economic growth of recipient countries. As such, there should be policies to avoid fungibility or to ensure the elimination of potential crowding out of usual government spending on development tasks due to political moral hazard.

In this paper, to measure aid concentration I have employed the commonly used concentration measure, Herfindahl-Hirschman index (HHI). However, one can argue that the right measure for the purpose would be Gini co-efficient or an entropy measure rather than HHI; see Davies (1979). These are typical inequality measures. “The Herfindahl-Hirschman Index (HHI) is the most widely treated summary measure of concentration in the theoretical literature and often serves as a benchmark for the evaluation of other concentration indices” (Bikker & Haaf, 2002, p. 7). “Concentration and Inequality are related concepts which have been historically confused… The most common measure of concentration has historically been the Herfindhal-Hirschman Index (HHI)...” (Ávila, Flores, López-Gallo, & Márquez, 2013, p. 3) Nevertheless, I repeated my analysis for the base model alternatively using Gini coefficient and Theil index as the measure of aid concentration; unreported results were strongly consistent with the original results.

There is only a limited number of different aid categories for which donors donate and a limited number of donors in the world with potential and willingness to donate. In addition, disasters are not evenly distributed across countries. As such, my study may not represent a universal picture. Further, it does not identify the exact mechanisms through which natural disasters influence aid concentration or aid concentration affects economic development. Future research can address these issues. As this paper too use nationally aggregate data, a possible improvement would be to repeat the analysis for case studies using microdata.

In the third and final empirical paper, I investigated the relationship between natural disasters on regional income inequality in Sri Lanka, a lower middle income country. Using a purpose-built panel dataset based on disaster affected population and inequality measures derived from a household income and expenditure survey series, I found that natural disasters decrease income inequality among Sri Lankan households. However, natural disasters do not affect household expenditure inequality. Further analysis showed that natural disasters decrease non-seasonal agricultural and non-agricultural income inequality but increase seasonal- agricultural income inequality. This was explained as the richer households mainly receive their income from non-agricultural and non-seasonal agricultural activities. In contrary, poorer households have a higher share of seasonal agricultural income compared to the rich.

My findings warrant policies to safeguard the interests of middle and higher income groups in disaster consequences. Generally, the desirable is the lower income inequality (McKay & Pal, 2004). However, the reduction in income inequality achieved at the expense of middle and high income earners does not reflect a true distributive justice. As such, policy makers should give due considerations to natural disasters as an important dimension when designing and implementing poverty reduction and inclusive growth oriented policies. Further, any income inequality reduction policy makers observe in disaster vulnerable developing economies should be read with caution.

Every effort has been exerted to include all monetary and non-monetary income derived from all sources, in calculations. However, free State services such as education and health the value of which cannot be imputed easily and exactly, are not included in the income. Further, the OECD modified equivalence scale which was used to arrive at per adult equivalent income/expenditure does not take into consideration some household characteristics, such as health status and disabilities of household members that affect specific household needs and capacities. These may pose biases in estimations, however, these are common issues to any household survey.

My data do not capture possible internal migration due to natural disasters which would otherwise have explained the decrease in income inequality. This would be a limitation of my analysis. Future research can address this issue although this study is constrained with data availability.

Further, recent research (Patankar, 2017) suggests that frequent urban and flash floods severely affect very poor individuals, especially, people who live in temporary huts, slums, shanties and single-storied buildings, repeatedly. It is believed that these events do not enter formal databases in the normal course, but their impact on poor people could be large, especially through health effects. Also, such disasters could negatively impact the income of the poor through missed days of work. This would cause biases in the estimations. Therefore, this analysis could be repeated with carefully collected broadened primary data.

Furthermore, Sri Lanka is just one country out of many which face various natural disaster consequences and issues relating to distributive justice at the same time. Therefore, to repeat this analysis for other countries would be another potential avenue for future research, for clarity.

My thesis showed that destructive natural disasters sometimes lead to unexpected outcomes. If we are prudent enough to recognise the true nature of unavoidable and destructive disaster consequences, it is possible to transform the threats of natural disasters into development efforts in order to enhance the development outlook of our economies.

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A Appendix to Chapter 2

Figure A.1: Percentage effect of natural disasters on per capita credit (using 2011 values)

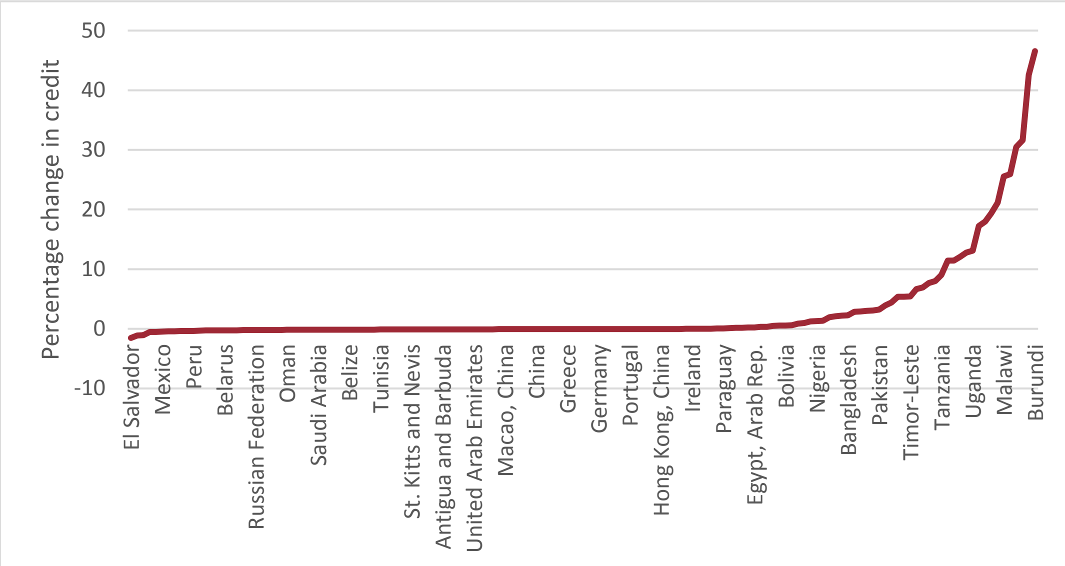

Figure A.2: Effect of natural disasters on per capita credit (%, using 2011 values)

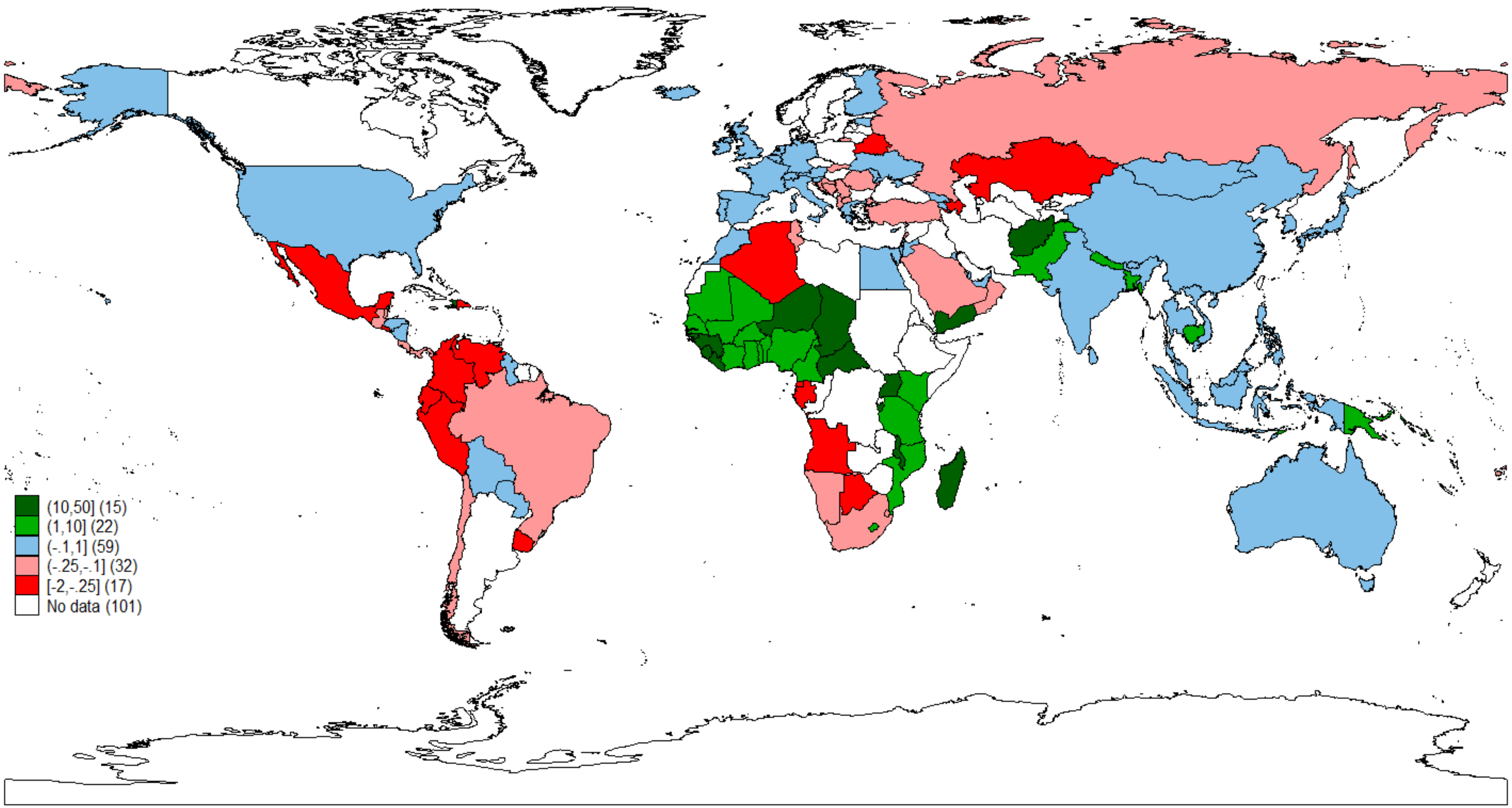

Table A.1: Average impact of natural disasters on credit in selected countries

Country	Avg. GDP pc ($)	$ Effect	SD	Avg. Credit pc ($)	%Effect	SD
Equatorial Guinea	4,279	-3.69	2.40	230	-1.61	1.04
El Salvador	2,310	-0.81	2.09	123	-0.66	1.70
Dominican Republic	2,953	-1.96	2.15	674	-0.29	0.32
Brazil	4,398	-3.82	2.42	1,427	-0.27	0.17
Ecuador	2,788	-1.69	2.12	635	-0.27	0.33
Namibia	3,261	-2.42	2.20	1,757	-0.14	0.12
Maldives	3,920	-3.28	2.32	3,005	-0.11	0.08
United States	35,998	-13.63	5.44	19,042	-0.07	0.03
Australia	27,780	-12.42	5.01	20,377	-0.06	0.02
Ireland	31,106	-12.95	5.20	34,841	-0.04	0.01
Sri Lanka	940	3.39	2.60	219	1.55	1.19
India	538	5.99	3.31	168	3.57	1.97
Pakistan	571	5.72	3.22	133	4.30	2.42
Yemen, Rep.	767	4.34	2.84	45	9.59	6.27
Mali	380	7.62	3.81	58	13.18	6.60
Nepal	268	9.24	4.35	62	15.00	7.06
Burkina Faso	326	8.33	4.05	48	17.47	8.49
Niger	297	8.77	4.19	33	26.35	12.60
Burundi	179	11.12	5.00	20	56.74	25.53
Guinea	289	8.90	4.24	13	66.29	31.57
Ethiopia	153	11.88	5.27	15	81.13	36.01
Congo, Dem. Rep.	380	7.62	3.81	4	188.83	94.54

Table A.2: Impact of natural disasters on credit in selected countries (using 2011 values)

Country	GDP pc ($)	Effect in $	SD	Credit pc ($)	% Effect	SD
El Salvador	2,997	-2.03	2.15	132	-1.53	1.63
Dominican Republic	4,927	-4.35	2.53	1,085	-0.40	0.23
Ecuador	3,449	-2.68	2.23	973	-0.28	0.23
Namibia	4,272	-3.68	2.39	2,052	-0.18	0.12
Brazil	5,721	-5.05	2.69	3,184	-0.16	0.08
Maldives	4,872	-4.30	2.52	3,866	-0.11	0.07
Thailand	3,158	-2.27	2.18	3,219	-0.07	0.07
United States	44,440	-14.62	5.80	23,386	-0.06	0.02
Australia	36,495	-13.70	5.47	44,270	-0.03	0.01
Ireland	45,385	-14.72	5.83	94,871	-0.02	0.01
Sri Lanka	1,725	0.55	2.13	461	0.12	0.46
India	1,086	2.71	2.45	512	0.53	0.48
Bangladesh	569	5.73	3.23	254	2.26	1.27
Pakistan	756	4.41	2.85	136	3.23	2.09
Nepal	385	7.56	3.79	192	3.93	1.97
Mali	497	6.36	3.42	96	6.65	3.57
Burkina Faso	463	6.69	3.52	87	7.70	4.05
Liberia	257	9.44	4.42	49	19.39	9.08
Niger	272	9.19	4.33	35	25.94	12.24
Guinea	304	8.65	4.16	20	42.57	20.44
Burundi	152	11.89	5.28	26	46.56	20.66

Table A.3: Models without the lagged dependent variable (fixed effects)

	Dependent variable: Credit per capita		
	(1)	(2)	(3)
Disaster	142.6**	226.9**	259.1**
	(63.29)	(110.6)	(125.3)
GDP per capita (in logs)	3,812*	3,513	3,029
	(2,299)	(2,336)	(1,906)
Disaster * ln GDP per capita	-18.65**	-30.75*	-34.88*
	(8.891)	(16.63)	(18.72)
Polity2		-467.8***	-479.1***
		(109.5)	(108.8)
Disaster * Polity2		2.38	2.78
		(1.80)	(2.15)
Inflation		0.37*	0.36*
		(0.21)	(0.20)
Disaster * Inflation		0.052	0.050
		(0.038)	(0.038)
Government Expenditure		219.6***	178.0**
		(77.04)	(72.86)
Disaster * Govt. Expenditure		-0.70	-1.14
		(2.03)	(2.02)
Trade Share			64.80
			(46.27)
Observations	4,352	3,564	3,558
R-squared	0.169	0.225	0.244
Number of Countries	177	151	151

Notes: Annual data 1979-2011. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.4: First difference linear estimator (all the variables are differenced except for disaster and GDP per capita)

	Dependant variable: Change in credit per capita										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Disaster	**56.79*** **	**71.08*** **	**71.48*** **	**71.58*** **	**70.76*** **	**70.77*** **	**72.17*** **	**73.63*** **	**73.68*** **	**73.58*** **	**72.42*** **
	(13.26)	(15.20)	(16.15)	(16.39)	(16.28)	(16.45)	(16.91)	(17.01)	(17.02)	(17.10)	(16.03)
GDP pc (in logs)	284.8***	297.0***	302.7***	306.7***	307.9***	307.5***	307.6***	307.7***	307.7***	307.8***	307.6***
	(40.25)	(43.63)	(46.71)	(47.30)	(47.53)	(47.26)	(47.27)	(47.30)	(47.31)	(47.32)	(47.20)
Dis * ln GDP pc	**-7.89*** **	**-10.30*** **	**-10.38*** **	**-10.34*** **	**-10.22*** **	**-10.22*** **	**-10.41*** **	**-10.59*** **	**-10.59*** **	**-10.57*** **	**-10.39*** **
	(1.88)	(2.20)	(2.33)	(2.35)	(2.33)	(2.35)	(2.41)	(2.43)	(2.43)	(2.46)	(2.30)
D. Polity2		-2.10	1.40	2.80	2.95	2.72	0.99	1.05	1.04	1.02	1.11
		(4.20)	(4.46)	(4.69)	(5.04)	(5.05)	(4.99)	(4.99)	(4.99)	(4.99)	(5.05)
D. Agriculture share			-0.32	0.01	1.84	3.47	3.45	2.97	2.98	3.19	3.60
			(3.45)	(3.54)	(3.88)	(4.78)	(4.78)	(4.75)	(4.75)	(4.78)	(5.7
D. Inflation				-0.0103	-0.0109	-0.0087	-0.0086	-0.0087	-0.0076	-0.0084	-0.0080
				(0.0073)	(0.0073)	(0.0075)	(0.0074)	(0.0074)	(0.0086)	(0.0082)	(0.0084)
D. Govt. Exp.					12.96	11.11	11.08	11.06	11.10	12.11	12.11
					(9.84)	(11.06)	(11.07)	(11.06)	(11.11)	(11.59)	(11.65)
D. Trade Share						4.94	4.97	4.98	4.98	5.02	5.37
						(5.63)	(5.64)	(5.64)	(5.64)	(5.65)	(6.04)
Dis * D. Polity2							0.84*	0.81	0.81	0.84*	0.71
							(0.50)	(0.50)	(0.50)	(0.50)	(0.49)
Dis * D. Agrshr								0.25	0.25	0.13	-0.05
								(0.31)	(0.31)	(0.32)	(0.41)
Dis * D. Inflation									-0.00131	6.69e-05	-0.000283
									(0.00296)	(0.00259)	(0.00255)
Dis * D. Govt. Exp.										-0.88	-0.79
										(0.97)	(0.96)
Dis* D. Trade Share											-0.186
											(0.248)
Observations	4,155	3,611	3,155	3,085	2,997	2,991	2,991	2,991	2,991	2,991	2,991
R-squared	0.090	0.170	0.166	0.168	0.170	0.171	0.171	0.171	0.171	0.171	0.171

Notes: Annual data 1979-2011, except where first observation lost due to differencing. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.5: Aggregated (ten-year) data

	Dependent variable: Credit per capita								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Disaster	**1,035***	**1,545****	**1,895*****	**2,141*****	**2,125*****	**1,978*****	**1,915*****	**2,269*****	**2,074*****
	(536)	(628)	(662)	(701)	(705)	(660)	(677)	(825)	(710)
GDP per capita (in logs)	4,824*	4,189	4,419	4,161	4,153	4,727*	4,694*	4,028**	3,820**
	(2,782)	(2,844)	(2,928)	(2,921)	(2,926)	(2,459)	(2,454)	(1,901)	(1,862)
Disaster * ln GDP per capita	**-133.6***	**-205.8****	**-259.9*****	**-289.9*****	**-288.6*****	**-271.7*****	**-273.8*****	**-297.5*****	**-240.7****
	(72.56)	(90.33)	(93.65)	(100.0)	(100.3)	(96.31)	(97.79)	(110.4)	(96.85)
Polity2		-496.9***	-557.1***	-610.8***	-608.9***	-680.2***	-684.5***	-648.5***	-631.4***
		(124.2)	(135.2)	(144.4)	(144.5)	(161.2)	(164.2)	(153.6)	(150.9)
Disaster * Polity2			29.84*	28.51	28.29	29.03	28.92	22.37	15.50
			(17.86)	(18.20)	(18.26)	(18.19)	(18.01)	(18.03)	(22.10)
Inflation				1.295	1.147	0.717	0.717	0.619	0.714
				(0.896)	(0.978)	(0.879)	(0.877)	(0.893)	(0.944)
Disaster * Inflation					0.144	0.263	0.273	0.358	0.289
					(0.280)	(0.244)	(0.244)	(0.288)	(0.285)
Government Expenditure						286.7**	275.9**	255.0**	230.3*
						(111.0)	(132.9)	(120.3)	(121.0)
Disaster * Govt. Expenditure							4.632	-10.79	3.244
							(17.26)	(20.66)	(18.35)
Trade Share								88.39	99.64
								(62.05)	(66.92)
Disaster * Trade									-5.486
									(3.947)
Observations	439	384	384	376	376	369	369	369	369
R-squared	0.184	0.238	0.241	0.253	0.253	0.272	0.272	0.298	0.302
Number of Countries	175	152	152	150	150	150	150	150	150

Notes: Aggregated data in periods, 1979-2008. All models include a constant term, country and time fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.6: Models without credit outliers (fixed effects)

	Dependent variable: Credit per capita					
	(1) w/o bot. 10%	(2) w/o top 10%	(3) w/o bot. & top 10%	(4) w/o bot. 20%	(5) w/o top 20%	(6) w/o bot. & top 20%
Disaster (% Pop. Affected)	51.31**	23.36**	36.61***	61.22**	6.906**	14.81**
	(20.29)	(10.09)	(11.99)	(26.54)	(3.339)	(6.991)
Lagged Credit per capita	0.998***	1.010***	1.007***	0.996***	1.021***	1.005***
	(0.0174)	(0.0222)	(0.0225)	(0.0175)	(0.0226)	(0.0226)
GDP per capita (in logs)	844.7***	361.4***	478.9***	1,012***	161.9***	270.9***
	(228.4)	(83.14)	(110.1)	(273.2)	(32.05)	(53.51)
Dis * ln GDP per capita	-6.545***	-3.072**	-4.644***	-7.912***	-0.893**	-1.919**
	(2.377)	(1.367)	(1.510)	(3.026)	(0.450)	(0.892)
Share of Agriculture	27.04**	5.739***	9.930***	38.30**	1.630*	3.887
	(11.40)	(2.136)	(3.425)	(17.06)	(0.929)	(2.521)
Disaster * Agriculture	-0.253	-0.0963**	-0.185**	-0.162	-0.0246	-0.0379
	(0.171)	(0.0437)	(0.0866)	(0.243)	(0.0162)	(0.0464)
Polity2	-0.575	3.091	2.627	-2.370	0.621	1.513
	(5.955)	(2.026)	(2.271)	(7.156)	(1.041)	(1.729)
Observations	2,794	2,840	2,445	2,447	2,617	1,875
R-squared	0.958	0.931	0.932	0.959	0.935	0.937
Number of Countries	144	141	138	131	125	109

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.7: Models without disaster outliers (fixed effects)

	Dependent variable: Credit per capita			
	(1) w/o top 27 obs	(2) w/o top 55 obs	(3) w/o yr 2004	(4) w/o yrs 2004-2005
Disaster (% Pop. Affected)	39.80**	37.32**	36.79***	39.07***
	(17.57)	(17.84)	(13.71)	(13.24)
Lagged Credit per capita	1.000***	1.000***	0.999***	1.000***
	(0.0172)	(0.0172)	(0.0182)	(0.0176)
GDP per capita (in logs)	662.2***	660.9***	687.1***	680.8***
	(177.6)	(178.3)	(181.5)	(174.6)
Dis * ln GDP per capita	-5.591**	-4.976**	-4.877***	-5.196***
	(2.192)	(2.208)	(1.745)	(1.666)
Share of Agriculture	15.56**	15.56**	16.63**	16.29**
	(6.989)	(7.021)	(7.338)	(7.110)
Disaster * Agriculture	-0.0922	-0.0965	-0.137*	-0.137*
	(0.137)	(0.145)	(0.0777)	(0.0799)
Polity2	-1.194	-1.229	-0.817	0.111
	(5.318)	(5.342)	(5.409)	(5.330)
Observations	3,178	3,168	3,053	2,918
R-squared	0.958	0.958	0.958	0.958
Number of Countries	147	147	147	147

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.8: Models with main control variables (fixed effects)

	Dependent variable: Credit per capita						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Disaster (% Pop. Affected)	38.28**	41.68***	41.12***	43.19***	36.56**	36.56**	36.86**
	(14.76)	(15.08)	(15.07)	(15.76)	(15.93)	(16.04)	(16.34)
Lagged Credit per capita	1.000***	0.999***	0.999***	1.000***	1.000***	1.000***	1.000***
	(0.0172)	(0.0172)	(0.0172)	(0.0174)	(0.0174)	(0.0178)	(0.0178)
GDP per capita (in logs)	656***	661***	660***	709***	711***	702***	703***
	(177)	(179)	(178)	(196)	(196)	(190)	(191)
Disaster * ln GDP per capita	-5.04***	-5.39***	-5.34***	-5.53***	-5.60***	-5.60***	-5.48**
	(1.87)	(1.91)	(1.90)	(1.97)	(2.0)	(2.01)	(2.15)
Share of Agriculture	15.70**	16.47**	16.43**	15.91*	15.79*	16.38*	16.43*
	(7.03)	(7.45)	(7.44)	(8.46)	(8.45)	(9.36)	(9.40)
Disaster * Agriculture	-0.15*	-0.18**	-0.19**	-0.22**	-0.16*	-0.16	-0.17*
	(0.082)	(0.083)	(0.083)	(0.091)	(0.091)	(0.096)	(0.088)
Polity2	-1.33	-1.02	-1.03	0.83	0.81	0.75	0.77
	(5.40)	(5.66)	(5.67)	(6.07)	(6.07)	(6.13)	(6.12)
Disaster * Polity2	0.11	0.09	0.08	0.12	0.11	0.12	0.10
	(0.10)	(0.10)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
Inflation		0.0106	0.0104	0.0117	0.0115	0.0102	0.0103
		(0.0182)	(0.0179)	(0.0193)	(0.0193)	(0.0183)	(0.0184)
Disaster * Inflation			0.0120	0.00983	0.0184	0.0176	0.0157
			(0.0157)	(0.0186)	(0.0175)	(0.0176)	(0.0174)
Government Expenditure				-9.67	-10.21	-10.17	-10.28
				(8.37)	(8.47)	(8.60)	(8.61)
Disaster * Govt. Expenditure					0.348	0.337	0.394
					(0.215)	(0.214)	(0.263)
Trade Share						1.23	1.26
						(4.16)	(4.19)
Disaster * Trade share							-0.017
							(0.03)
Observations	3,189	3,130	3,130	3,047	3,047	3,041	3,041
R-squared	0.958	0.958	0.958	0.958	0.958	0.958	0.958
Number of Countries	147	145	145	145	145	145	145

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.9: Models with further control variables (fixed effects)

	Dependent variable: Credit per capita					
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster (% Population Affected)	8.20**	44.38**	26.92**	24.17**	23.50**	4.82*
	(3.19)	(22.30)	(13.52)	(11.19)	(9.63)	(2.79)
Lagged Credit per capita	0.846***	1.012***	1.021***	1.040***	1.084***	1.014***
	(0.052)	(0.022)	(0.013)	(0.017)	(0.022)	(0.028)
GDP per capita (in logs)	239***	1,120***	548***	348***	64	138***
	(70.7)	(337.6)	(146.4)	(101.8)	(138.0)	(36.1)
Disaster * ln GDP per capita	-1.12***	-5.83**	-3.64**	-3.32**	-3.36***	-0.63
	(0.42)	(2.68)	(1.74)	(1.47)	(1.24)	(0.39)
Share of Agriculture	3.34**	28.93**	9.74*	7.58	1.72	0.64
	(1.52)	(13.23)	(5.03)	(5.42)	(5.24)	(0.71)
Disaster *Agriculture	-0.034	-0.219	-0.101	-0.097	-0.075	-0.017
	(0.023)	(0.189)	(0.073)	(0.059)	(0.055)	(0.014)
Polity2		-7.84	3.85	5.21	10.48*	0.48
		(8.65)	(5.55)	(4.09)	(5.52)	(0.94)
Non-life Insurance Premia (% GDP)		-96.92				
		(84.43)				
Financial Sector Rating	49.69*					
	(25.87)					
Lending Interest Rate			0.892			
			(0.547)			
Share of Resource Rent (% GDP)				-578**		
				(257)		
Share of Forestry Rent (% GDP)					5.15e-09	
					(4.90e-08)	
Disaster * Polity2						0.013
						(0.023)
Official Dev. Assistance (% GNI)						0.393
						(0.490)
Observations	424	2,157	2,452	2,341	2,814	2,415
R-squared	0.891	0.950	0.957	0.955	0.963	0.954
Number of Countries	71	140	138	129	139	112

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.10: Quantile regression results

	Dependent Variable: Credit per capita		
	(1) Q25	(2) Q50	(3) Q75
Disaster (% Pop. Affected)	290***	974***	1,455***
	(69.1)	(165.5)	(524.2)
GDP pc (in logs)	1,190***	3,595***	7,536***
	(185.9)	(244.4)	(312.8)
Disaster * ln GDP per capita	-37.4***	-121.8***	-192.0***
	(8.58)	(20.00)	(62.18)
Share of Agriculture	37.2***	148.2***	326.3***
	(7.52)	(15.52)	(33.75)
Disaster * Agriculture	-1.36***	-5.43***	-6.07
	(0.43)	(1.34)	(4.02)
Polity2	6.62**	36.94***	89.86***
	(3.35)	(10.42)	(26.63)
Observations	3,323	3,323	3,323
Pseudo R^2	0.0761	0.1591	0.3514

Notes: Annual data 1979-2011 and all models include a constant term. Simultaneous quantile regression bootstrap (100) SEs. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.11: Controlling for prices across space (variables in PPP constant 2005 US$, fixed effects)

	(1)	(2)
	Dep.var.: Credit per capita	Dep.var.: Logged credit per capita
Disaster (% Population Affected)	30.05**	0.0105*
	(13.57)	(0.00531)
Lagged Credit per capita	0.995***	
	(0.0124)	
Lagged Credit per capita (in logs)		0.833***
		(0.0244)
GDP per capita (in logs)	710.1***	0.297***
	(168.3)	(0.0439)
Disaster * ln GDP per capita	-3.553**	-0.00133**
	(1.587)	(0.000605)
Share of Agriculture	13.84**	-0.00491**
	(6.382)	(0.00215)
Disaster * Agriculture	-0.111	-4.46e-05
	(0.0763)	(3.96e-05)
Polity2	-3.539	0.000748
	(4.945)	(0.00191)
Observations	3,101	3,101
R-squared	0.957	0.916
Number of Countries	140	140

Notes: Annual data 1979-2011, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.12: Natural disasters in different geographical regions 1

	Dependent variable: Credit per capita			
	(1) Asia	(2) Africa	(3) Europe	(4) Americas
Disaster (% pop. affected)	128.3*	-0.294	-519.2	-79.93
	(64.91)	(1.215)	(470.5)	(89.76)
Lagged Credit per capita	0.942***	1.009***	0.980***	0.877***
	(0.0214)	(0.0339)	(0.0211)	(0.0173)
GDP per capita (in logs)	963.7**	56.17**	1,925**	755.1***
	(382.7)	(21.75)	(945.0)	(203.9)
Disaster * ln GDP per capita	-15.78*	0.0158	48.42	9.750
	(8.140)	(0.184)	(45.57)	(11.64)
Share of Agriculture	17.86	0.111	107.2**	-3.246
	(19.83)	(0.414)	(49.93)	(5.192)
Disaster * Agriculture	-0.722*	0.00937	6.670	0.370
	(0.382)	(0.00687)	(6.456)	(0.275)
Polity2	7.250	-0.448	-120.1**	8.775*
	(9.135)	(0.458)	(52.32)	(4.563)
Observations	772	1,119	669	494
R-squared	0.923	0.957	0.965	0.901
Number of Countries	37	47	35	23

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.13: Natural disasters in different geographical regions 2

	Dependent variable: Credit per capita						
	(1) East Asia & Pacific	(2) Europe & Central Asia	(3) Western Europe & N. America	(4) Latin America & Caribbean	(5) Middle East & N. Africa	(6) South Asia	(7) Sub-Saharan Africa
Disaster (% population affected)	192.9**	90.74	16,049	5.333	-376.6	-6.183	-0.538
	(78.04)	(55.60)	(18,446)	(10.05)	(727.4)	(6.983)	(1.164)
Lagged Credit pc	0.992***	1.001***	0.955***	0.921***	0.721***	1.138***	1.017***
	(0.0207)	(0.0171)	(0.0326)	(0.0390)	(0.0725)	(0.129)	(0.0384)
GDP pc (in logs)	809.7*	320.1	13,440**	550.2***	-658.5	52.19	52.21**
	(399.1)	(220.6)	(5,557)	(155.2)	(706.7)	(33.92)	(23.78)
Disaster * ln GDP pc	-23.24**	-11.00	-1,529	-1.360	52.16	0.656	0.0510
	(8.629)	(7.056)	(1,722)	(1.337)	(95.13)	(1.059)	(0.176)
Share of Agriculture	-4.922	25.10***	469.5*	-4.120	9.567	-0.945**	0.238
	(28.24)	(6.295)	(268.1)	(5.192)	(6.698)	(0.315)	(0.364)
Disaster * Agriculture	-0.947	-0.603	-67.65	0.144*	-1.296	0.0821	0.00974
	(0.563)	(0.378)	(256.0)	(0.0791)	(1.957)	(0.0582)	(0.00750)
Polity2	5.582	-20.15**	-156.1	8.145**	-49.84*	0.709	-0.192
	(8.888)	(9.008)	(283.8)	(3.715)	(26.55)	(0.905)	(0.387)
Observations	461	387	420	477	270	172	1,002
R-squared	0.967	0.976	0.970	0.912	0.668	0.974	0.956
Number of Countries	18	24	20	21	16	6	42

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.14: Pair-wise correlation between different disaster subgroups

	All Disasters	Biological	Climatic	Hydrological	Geophysical	Meteorological
All Disasters	1.0000					
Biological	0.0795	1.0000				
Climatic	0.7552	0.0131	1.0000			
Hydrological	0.2671	0.0012	0.0023	1.0000		
Geophysical	0.1321	0.0732	-0.0006	-0.0024	1.0000	
Meteorological	0.5825	-0.0012	-0.0026	0.0136	-0.0024	1.0000

Table A.15: Different disaster subgroups – baseline specification

	Dependent variable: Credit per capita
	Fixed Effects
Biological Disasters (% Population Affected)	422.2**
	(210.9)
Climatic Disasters (% Population Affected)	34.02**
	(16.02)
Geophysical Disasters (% Population Affected)	569.8***
	(199.6)
Hydrological Disasters (% Population Affected)	24.65
	(39.89)
Meteorological Disasters (% Population Affected)	-10.95
	(34.22)
Lagged Credit per capita	1.000***
	(0.0173)
GDP per capita (in logs)	661.8***
	(178.5)
Biological * ln GDP per capita	-54.65*
	(28.64)
Climatic * ln GDP per capita	-4.551**
	(2.147)
Geophysical * ln GDP per capita	-71.10***
	(24.27)
Hydrological * ln GDP per capita	-3.354
	(4.886)
Meteorological * ln GDP per capita	1.281
	(4.191)
Share of Agriculture	15.65**
	(7.033)
Biological * Agriculture	-2.394*
	(1.289)
Climatic * Agriculture	-0.133*
	(0.0799)
Geophysical * Agriculture	-2.807***
	(1.063)
Hydrological * Agriculture	0.0593
	(0.384)
Meteorological * Agriculture	0.116
	(0.238)
Polity2	-1.081
	(5.310)
Observations	3,189
Number of Countries	147
R-squared	0.958

Notes: Annual data 1979-2011, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.16: Regressions without biological disasters (alternative estimators)

	Dependent variable: Credit per capita		
	(1)	(2)	(3)
	Fixed Effects	OLS	System GMM
Disasters without Bio (% Pop. Affected)	33.62**	62.31***	110.4**
	(14.08)	(16.42)	(54.12)
Lagged Credit per capita	1.000***	1.027***	0.962***
	(0.0172)	(0.00714)	(0.0195)
GDP per capita (in logs)	652.7***	228.6***	556.4***
	(176.2)	(53.69)	(182.7)
Disaster without Bio * ln GDP per capita	-4.457**	-7.787***	-14.69**
	(1.814)	(1.966)	(6.880)
Share of Agriculture	15.61**	13.32***	24.85***
	(7.005)	(3.583)	(8.001)
Disaster without Bio * Agriculture	-0.127*	-0.328***	-0.438
	(0.0756)	(0.110)	(0.436)
Polity2	-1.104	6.390**	26.83**
	(5.273)	(2.698)	(12.95)
Observations	3,189	3,189	3,189
R-squared	0.958	0.992	
Number of Countries	147		147
Number of Instruments			109
Arellano-Bond Test AR(1)			0.278
Arellano-Bond Test AR(2)			0.053
Arellano-Bond Test AR(3)			0.156
Arellano-Bond Test AR(4)			0.283
Hansen Test			0.841

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 No. of lags used to instrument the endogenous disaster variables in system GMM regression limited to 10 starting at lag 3.

Table A.17: Using binary disaster variable with different thresholds (baseline, fixed effects)

	Dependent variable: Credit per capita								
	Different thresholds used on the percentage of population affected by disasters to isolate severe disasters								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	> 0	> 0.5%	> 1%	> 2.5%	> 5%	> 5.5%	> 6%	> 7.5%	> 10%
Disaster Dummy	181.8	256.2	326.1	449.3	558.0	875.2**	935.2**	748.1**	1,006**
	(813.1)	(503.4)	(346.1)	(331.3)	(394.7)	(399.5)	(404.8)	(369.9)	(400.1)
Lagged Credit pc	0.999***	1.000***	0.999***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
	(0.0172)	(0.0172)	(0.0173)	(0.0172)	(0.0172)	(0.0172)	(0.0172)	(0.0172)	(0.0172)
ln GDP pc	648.7***	650.7***	653.0***	655.9***	655.8***	660.0***	659.4***	654.8***	655.2***
	(198.7)	(173.9)	(174.6)	(175.6)	(174.5)	(175.1)	(175.1)	(176.7)	(176.9)
Dis * ln GDP pc	-24.52	-35.40	-50.02	-69.25*	-83.03*	-119.9**	-126.5**	-102.3**	-130.9***
	(99.12)	(63.82)	(43.90)	(40.63)	(49.41)	(50.60)	(51.21)	(46.23)	(48.71)
Agri. Share	16.88**	15.50**	15.29**	15.19**	15.32**	15.52**	15.58**	15.50**	15.60**
	(7.839)	(6.882)	(6.810)	(6.882)	(6.891)	(6.929)	(6.946)	(6.985)	(6.999)
Dis * Agri.	-2.023	-0.784	0.0314	0.802	-0.185	-2.599	-3.250	-2.160	-3.959
	(5.226)	(3.298)	(2.598)	(2.875)	(3.173)	(3.130)	(3.115)	(2.861)	(3.123)
Polity2	-1.414	-1.368	-1.408	-1.477	-1.226	-1.153	-1.206	-1.191	-1.198
	(5.134)	(5.236)	(5.251)	(5.277)	(5.304)	(5.301)	(5.293)	(5.278)	(5.279)
Observations	3,189	3,189	3,189	3,189	3,189	3,189	3,189	3,189	3,189
R-squared	0.958	0.958	0.958	0.958	0.958	0.958	0.958	0.958	0.958
Countries	147	147	147	147	147	147	147	147	147

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.18: Binary disaster variable without disaster-agriculture interaction (fixed effects)

	Dependent variable: Credit per capita								
	Different thresholds used on the percentage of population affected by disasters to isolate severe disasters for analysis								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	>0%	>0.5%	>1%	>2.5%	>5%	>5.5%	>6%	>7.5%	>10%
Disaster Dummy	10.60	184.9	328.9*	521.0***	541.5**	638.2***	637.1***	544.9**	645.7***
	(398.6)	(244.8)	(189.6)	(180.7)	(213.2)	(229.6)	(233.8)	(224.7)	(231.3)
Lagged Credit pc	0.999***	1.000***	0.999***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
	(0.0172)	(0.0172)	(0.0172)	(0.0172)	(0.0172)	(0.0172)	(0.0172)	(0.0172)	(0.0172)
GDP pc (in logs)	638.1***	649.0***	653.0***	656.8***	655.6***	657.6***	656.5***	652.8***	651.6***
	(185.6)	(174.4)	(175.6)	(176.2)	(175.3)	(175.6)	(175.4)	(176.6)	(176.5)
Dis * ln GDP pc	-7.212	-27.83	-50.32*	-76.94***	-81.25**	-94.28***	-94.23***	-80.21**	-92.04***
	(57.67)	(37.31)	(29.06)	(26.61)	(32.32)	(34.97)	(35.57)	(33.40)	(34.28)
Agri. Share	15.53**	15.30**	15.29**	15.30**	15.30**	15.27**	15.28**	15.33**	15.33**
	(7.043)	(6.979)	(6.965)	(6.970)	(6.970)	(6.969)	(6.970)	(6.980)	(6.977)
Polity2	-1.413	-1.373	-1.408	-1.473	-1.229	-1.202	-1.253	-1.229	-1.252
	(5.133)	(5.234)	(5.244)	(5.272)	(5.291)	(5.287)	(5.283)	(5.269)	(5.273)
Observations	3,189	3,189	3,189	3,189	3,189	3,189	3,189	3,189	3,189
R-squared	0.958	0.958	0.958	0.958	0.958	0.958	0.958	0.958	0.958
Number of Countries	147	147	147	147	147	147	147	147	147

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.19: Impact disaster variable

	Dependent variable: Credit per capita	
	(1)	(2)
	Intensity>0.0001	Severe Intensity>0.01
Disaster Impact Variable	-1,220	-1,750
	(991.4)	(1,567)
Lagged Credit per capita	1.000***	1.000***
	(0.0171)	(0.0171)
GDP per capita (in logs)	529.8***	550.6***
	(147.1)	(146.4)
Disaster * ln GDP per capita	141.4	207.5
	(115.7)	(188.8)
Share of Agriculture	7.880	10.19*
	(6.017)	(5.536)
Disaster * Agriculture	9.806	14.31
	(7.435)	(11.23)
Polity2	-1.376	-1.811
	(5.279)	(5.463)
Observations	3,189	3,189
R-squared	0.958	0.958
Number of Countries	147	147

Notes: Annual data 1979-2011, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.20: Impact disaster variable with limited controls

	Dependent variable: Credit per capita			
	(1)	(2)	(3)	(4)
	Intensity>0.0001	Intensity>0.01	Intensity>0.05	Intensity>0. 1
Disaster Impact Variable	49.55	84.73	102.7	98.99
	(62.75)	(68.72)	(76.92)	(78.37)
Lagged Credit per capita	0.995***	0.994***	0.994***	0.994***
	(0.0232)	(0.0232)	(0.0232)	(0.0232)
GDP per capita (in logs)	658.3**	649.3**	643.9**	643.3**
	(314.4)	(311.0)	(309.1)	(308.9)
Observations	4,155	4,155	4,155	4,155
R-squared	0.943	0.943	0.943	0.943
Number of Countries	176	176	176	176

Notes: Annual data 1979-2011, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.21: Weighed disaster variable

	Dependent variable: Credit per capita
	Fixed Effects
Disaster (% Pop. affected, adjusted for onset month)	28.09
	(17.37)
Lagged Credit per capita	1.003***
	(0.0230)
GDP per capita (in logs)	361.7***
	(129.5)
Disaster * ln GDP per capita	-3.308
	(2.102)
Share of Agriculture	4.606
	(5.620)
Disaster * Agriculture	-0.144
	(0.131)
Polity2	2.705
	(5.998)
Observations	2,100
Number of Countries	141
R-squared	0.975

Notes: Annual data 1979-2011, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.22: Liquid assets to deposits and short term funding (%) as the dependent variable

	Dependent variable: Liquid assets to deposits & short term funding (%)
	Fixed Effects
Disaster (% pop. affected)	1.961**
	(0.848)
LDV	0.665***
	(0.0554)
GDP pc (in logs)	-8.415**
	(3.306)
Disaster * ln GDP pc	-0.237**
	(0.103)
Share of Agriculture	0.130
	(0.102)
Disaster * Agriculture	-0.0149**
	(0.00687)
Polity2	-0.122
	(0.143)
Observations	1,734
R-squared	0.475
Number of Countries	148

Notes: Annual data 1979-2011, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.23: Indicators for financial depth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	gfdd_di_02	gfdd_di_03	gfdd_di_08	gfdd_di_09	gfdd_di_10	gfdd_dm_01	gfdd_dm_02	gfdd_dm_03	gfdd_dm_04	gfdd_dm_07
Disaster	0.0815	-0.282	0.0720	-0.0242	-0.00917	-0.530	3.320	-0.754**	-0.865**	-0.519
	(0.116)	(0.186)	(0.0810)	(0.0218)	(0.00922)	(0.627)	(3.476)	(0.356)	(0.379)	(0.519)
Dis * ln GDP pc	-0.0115	0.0353	-0.0107	0.00204	0.00145	0.0653	-0.361	0.0840**	0.0893**	0.0553
	(0.0142)	(0.0212)	(0.00987)	(0.00271)	(0.00108)	(0.0752)	(0.394)	(0.0347)	(0.0370)	(0.0590)
Observations	3,193	873	3,176	2,050	2,272	1,572	1,540	705	828	1,040
R-squared	0.929	0.947	0.907	0.666	0.810	0.621	0.571	0.928	0.942	0.948
No. of Countries	148	56	147	140	144	100	99	43	48	82

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1, gfdd_di_02 – Deposit money banks' assets to GDP (%), gfdd_di_03 – Nonbank financial institutions' assets to GDP (%), gfdd_di_08 – Financial system deposits to GDP (%), gfdd_di_09 – Life insurance premium volume to GDP (%), gfdd_di_10 – Nonlife insurance premium volume to GDP (%), gfdd_dm_01 – Stock market capitalisation to GDP (%), gfdd_dm_02 – Stock market total value traded to GDP (%), gfdd_dm_03 – Outstanding domestic private debt securities to GDP (%), gfdd_dm_04 – Outstanding domestic public debt securities to GDP (%), gfdd_dm_07 – International debt issues to GDP (%)

Table A.24: Indicators for financial access

	(1) gfdd_ai_01	(2) gfdd_ai_02	(3) gfdd_am_01	(4) gfdd_am_02	(5) gfdd_am_03
Disaster	0.535	0.0356	0.679	-0.497	0.136
	(8.587)	(0.0400)	(2.795)	(2.326)	(0.285)
Disaster * ln GDP per capita	-0.487	-0.00696	-0.107	0.0418	-0.0130
	(1.396)	(0.00611)	(0.293)	(0.259)	(0.0285)
Observations	347	844	443	450	219
R-squared	0.683	0.526	0.397	0.419	0.841
Number of Countries	62	131	43	43	23

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1, gfdd_ai_01 – Bank accounts per 1000 adults, gfdd_ai_02 – Bank branches per 100,000 adults, gfdd_am_01 – Value traded excluding top 10 traded companies to total value traded (%), gfdd_am_02 – Market capitalisation excluding top 10 companies to total market capitalisation (%), gfdd_am_03 – Nonfinancial corporate bonds to total bonds and notes outstanding (%)

Table A.25: Indicators for financial efficiency

	(1) gfdd_ei_01	(2) gfdd_ei_02	(3) gfdd_ei_03	(4) gfdd_ei_04	(5) gfdd_ei_05	(6) gfdd_ei_06	(7) gfdd_ei_09	(8) gfdd_ei_10	(9) gfdd_em_01
Disaster	0.0897	0.113	0.133	-0.0147	-0.251	0.626	-0.275	0.741	1.156
	(0.172)	(0.119)	(0.463)	(0.0986)	(0.237)	(1.465)	(0.251)	(1.974)	(1.130)
Disaster * ln GDP pc	-0.0103	-0.0133	-0.0295	0.000569	0.0306	-0.0625	0.0338	-0.0641	-0.101
	(0.0197)	(0.0138)	(0.0602)	(0.0115)	(0.0282)	(0.168)	(0.0298)	(0.224)	(0.134)
Observations	1,575	2,521	1,710	1,580	1,581	1,578	1,581	1,578	1,531
R-squared	0.113	0.524	0.309	0.154	0.033	0.101	0.038	0.114	0.476
Number of Countries	147	140	148	147	147	147	147	147	99

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1, gfdd_ei_01 – Bank net interest margin (%), gfdd_ei_02 – Bank lending-deposit spread, gfdd_ei_03 – Bank noninterest income to total income (%), gfdd_ei_04 – Bank overhead costs to total assets (%), gfdd_ei_05 – Bank return on assets (%, after tax), gfdd_ei_06 – Bank return on equity (%, after tax), gfdd_ei_09 – Bank return on assets (%, before tax), gfdd_ei_10 – Bank return on equity (%, before tax), gfdd_em_01 – Stock market turnover ratio (%)

Table A.26: Indicators for financial stability

	(1) ln(gfdd_si_01)	(2) gfdd_si_02	(3) gfdd_si_03	(4) gfdd_si_04	(5) gfdd_si_05	(6) gfdd_si_07	(7) gfdd_sm_01
Disaster	-0.0151	-0.0242	0.464	-0.118	0.412	2.462	0.856
	(0.0306)	(0.304)	(0.309)	(0.420)	(0.507)	(3.100)	(0.903)
Disaster * ln GDP per capita	0.0012	-0.00726	-0.0517	-0.00162	-0.0442	-0.156	-0.0782
	(0.0037)	(0.0361)	(0.0369)	(0.0514)	(0.0548)	(0.363)	(0.0907)
Observations	1,531	1,012	997	3,630	1,019	870	1,092
R-squared	0.188	0.653	0.464	0.740	0.378	0.502	0.645
Number of Countries	142	96	96	149	96	95	75

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1, gfdd_si_01 – Bank Z-score, gfdd_si_02 – Bank nonperforming loans to gross loans (%), gfdd_si_03 – Bank capital to total assets (%), gfdd_si_04 – Bank credit to bank deposits (%), gfdd_si_05 – Bank regulatory capital to risk-weighted assets (%), gfdd_si_06 – Liquid assets to deposits and short term funding (%), gfdd_si_07 – Provisions to nonperforming loans (%), gfdd_sm_01 – Stock price volatility